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Gender recognition using optimal gait feature based on recursive feature elimination in normal walking

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ABSTRACT

This study aims to propose a novel approach for gender recognition using best feature subset based on recursive feature elimination (RFE) in normal walking. This study has focused on the analysis of gait characteristics by distinguishing the gait phases as initial contact (IC), Mid-stance (MS), Pre-swing, and swing (SW), and collected the large number of gait to improve the reliability of quantitative assessment of natural variability associated with muscle activity during free walking. The gait system was designed using pressure and a tri-axis accelerometer sensor, and a 9-channel electromyography sensor for measuring the data. Gender recognition method was proposed using support vector machine (SVM) and random forest (RF) based on RFE to determine best feature subset. Statistical results show that effects of gender-based differences on gait characteristic including temporal, kinematics, and muscle activity were investigated. The temporal parameters of stride time and gait cycle (%) in the gait phases of IC, MS, and SW were significantly different between females and males ($p<0.01$). The females exhibited both a lower angle and a root mean square acceleration of the knee joint as compared to the males, and there was a clear gender-based difference with respect to knee angle movement. In addition, most muscle activation measurements in the females were larger than those of the males with respect to the gait phases. Gender classification result shows that SVM-RFE was 99.11% (SVM classifier) and RF-RFE was 98.89% (SVM and RF classifier), having powerful performance.

1. Introduction

Gender information can be applied to healthcare, smart spaces, security, marketing, human–machine interactions, and biometric-based control applications. For example, gender information helps improve the performance of security systems based on biometrics. Jain, Dass, and Nandakumar (2004) improved the identification performance of a fingerprint system by utilizing soft biometric traits containing gender information. In addition, gender information can be utilized in advanced intelligent spaces that can be customized to provide an enhanced user experience (Jain & Kanhangad, 2018), and advanced intelligent spaces containing market product preferences, advertisements, marketing, and recommendation systems can be based on gender information. Gender information can be extracted using raw signals, such as text, images, videos, bio-signals, and physical signals. Most of the sensors that collect these signals can be used in smartphones with built-in sensors or be developed as wearable sensors and embedded in smart environments in consumer markets (Dong, Du, & Cai, 2020). Since various wearable sensors capable of acquiring these signals have been recently developed, there is no difficulty in constructing a customized smart space. However, it is still a challenge to study automated gender classification based on user bio-signals.

Above all, the most important reason for gender recognition based on EMG signals can be explained as follows. Many studies have adopted surface EMG signals for recognizing the gait cycle to control lower extremity exoskeletons and powered prostheses, and EMG signals can be used to control kinetic loading on rehabilitation machines in stepping exercises (Rosli et al., 2017) or rehabilitation activities (Nazmi et al., 2015). The EMG-based system interface should include a function that can identify a gender because the muscle activation and preferred speeds of men and women are different, and different loads or appropriate feedback should be applied depending on muscle fatigue or muscle activity on gender difference (Miller et al., 1993). Therefore, for an advanced rehabilitation system and a powered prosthesis, a function that can automatically recognize gender through gait information obtained from an EMG sensor and provide feedback on muscle activity and muscle fatigue according to gender is required.

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According to anthropometric measurements of female and male groups (Cho, Park, & Kwon, 2004), there are distinct gender-based differences in skeletal dimensions and characteristics. It has been hypothesized that gait patterns may differ between genders. These differences in gait are of interest for a variety of clinical and medical applications. In pathology, the differences in gait characteristics between the gender groups exist and influence incidence rates (Bruening et al., 2015) of osteoarthritis (McKean et al., 2007), anterior cruciate ligament injury (Prodromos et al., 2007), pelvic motion (Smith, Lelas, & Kerrigan, 2002) and lower back pain (Fillingim et al., 2009; Nadler et al., 2000). These gender-based differences in various aspects of pathology affect strategies for the treatment and rehabilitation of muscle and joint diseases by gender (Bruening et al., 2015). In the field of rehabilitation, the gait characteristics between gender groups can also be applied to the design of a robotic assistance exoskeleton and powered prosthesis for walking rehabilitation. In addition, gender-based differences during walking may be applied in various industries including physical therapy, Alzheimer's disease, targeted advertising, surveillance and tracking, activity recognition, electrocardiography analysis, stress measurement and security.

The purpose of the present study was to analyze temporal, kinematic, and muscle activation-related gait characteristics in adult men and women walking at preferred speeds. In addition, we propose a robust method based on the best feature subset using recursive feature elimination to improve the performance of gender classification.

A proposed gait system was designed to measure gait sub-phases and knee angle using two pressure sensors and a tri-axis accelerometer sensor. A nine-channel EMG sensor was then synchronized with the gait system to obtain quantitative data. The key contributions of our work are as follows:

- To the best of our knowledge, our method based on the classification of gait sub-phases represents the first attempt at gender recognition.
- The proposed gender classification approach provides additional information on gait sub-phases in terms of various gait characteristics, such as the muscles frequently used in specific gait steps.
- The proposed approach based on recursive feature elimination supports a system that automatically determines the optimal features with the highest ranking among the various signals and many features in the training stage.

The remainder of this paper is organized as follows. Section 2 discusses the related works, and Section 3 introduces our database. Section 4 presents the method for analyzing gender-based gait characteristics and the proposed gender classification method. Statistical results and classification performance of proposed method are presented in Section 5, and Section 5 discusses about the interpretation of the experiments. Section 6 draws the study conclusions.

2. Related works

2.1. Gender-based difference in gait

In the past few years, several studies have evaluated gender-based differences in gait by using gait characteristics. These studies show that gait parameters exhibit differences between male and female groups, and that it is possible to analyze gait patterns between these two groups. Gait characteristics are mainly classified on the following parameters: (i) time and spatiotemporal, (ii) kinematic, and (iii) muscle activation. With respect to the time and spatiotemporal parameters, Ryu et al. (2006) have demonstrated that spatio-temporal gait parameters such as stride width, walking speed, stride length, step length, and swing time in the female group were found to be smaller than those in the male group. Cho et al. (2004), Kadaba, Ramakrishnan, and Wootten (1990), and Ryu et al. (2006) have reported that the cadence of women was greater than that of men. Similarly, a study analyzing gender- and age-based differences using raw accelerometer data has also been performed (Auvinet et al., 2002).

With respect to kinematic parameters, Bruening et al. (2015) have reported that females demonstrate greater parameter values including pelvic obliquity, transverse plane pelvis, torso rotation, arm swing, hip, and ankle as compared to men. In addition, the range of motion (ROM) of the pelvis in females is greater than that in males, and there is a significant gender difference (Chockalingam et al., 2012; Chumanov, Wall-Scheffler, & Heiderscheit, 2008; Ryu et al., 2006). Crosbie, Vachalathiti, and Smith (1997) and Smith et al. (2002) reported conflicting results regarding gender differences with respect to walking. Nonetheless, on statistical analysis, it has been shown that there are no significant gender-based differences in walking. Knee joint kinetics have also been studied and females exhibit smaller ROM values at the knee and a smaller knee flexion motion pattern when compared to males (Bruening et al., 2015; Decker et al., 2002; Lephart et al., 2002; Malinzak et al., 2001) during athletic tasks. The evaluation of muscle activation patterns using electromyography (EMG) suggests that females demonstrate higher tibialis anterior muscle activity than males during normal walking (Chiu & Wang, 2007). In addition, muscle activation of quadriceps, medial hamstring, and lateral hamstring in female group were greater than those of male groups in studies of side-step cutting (Sigward & Powers, 2006). Although there have been many studies, there is still no consensus on whether gender-based differences exist in gait characteristics. To more accurately and precisely investigate the gait characteristics of male and female groups,we hypothesis that more gait information can be obtained in gait sub-phases and conduct to investigate gait information in sub-phases.

2.2. Gender classification using machine learning techniques

Many studies have developed the method for gender classification using machine learning techniques as shown in Table 1. Gender analysis studies based on gait characteristics have used various sensors such as cameras, accelerometer, gyroscope, electromyography (EMG), and foot pressure sensors, depending on the field in which it is utilized. Weiss and Lockhart (2011) proposed a method to recognize the gender in 64 subjects using 43 statistical features extracted from the accelerometer and gyroscope data of the smartphone. Jain and Kanhangad (2016, 2018) presented a gender classification method using gait features with bagging classifier and they utilized the smartphone for acquiring accelerometer and gyroscope data. Dong et al. (2020) proposed a method of motion features with four supervised learning methods using smartphone. Ahmed and Sabir (2017) used kinect sensor for gender classification and they proposed the method of dynamic distance feature with neural network and supervised learning classifiers. Barra et al. (2019) introduced the method of gender recognition using camera of smartphone based on 2D estimated skeleton points with random forest classifier. Due to the differences in the types of sensors and databases used, it is difficult to generalize the comparison of performances of the studies in Table 1 with the proposed method in this study. Although there are many studies on gender classification, to the best of our knowledge, ours is the first to propose a method of gender recognition based on the classification of gait sub-phases. This study provides additional information on various gait characteristics, such as the muscles frequently used in specific gait stages (for example, the muscles of the vastus medialis and tibialis posterior are the most active in the initial contact phase among the gait sub-phases (Ryu, Lee, & Kim, 2016)). Using information on gait sub-phases, this study developed a robust method of determining the optimal gait feature subset for gender recognition.

Table 1
A summary of the state-of-the-art for gender classification using gait parameter.

Publication	Sensor	Modality	Dataset	Method
Weiss and Lockhart (2011)	Smartphone (accelerometer sensor)	Gait	38 males and 28 females	Statistical features with NN, IB3 and J48 classifiers
Jain and Kanhangad (2016)	Smartphone (accelerometer sensor)	Gait	25 males and 17 females	Multi-level local pattern based features with bagging classifier
Jain and Kanhangad (2018)	Smartphone (accelerometer sensor)	Gait	25 males and 21 females	Histogram of gradient method with bagging classifier
Dong et al. (2020)	Smartphone (accelerometer and gyroscope sensor)	Gait	28 males and 28 females	Motion features with four supervised learning methods
Ahmed and Sabir (2017)	Kinect sensor	Gait	9 males and 9 females	Dynamic distance feature with NN, linear discriminant and support vector machine classifiers
Barra et al. (2019)	Smartphone (camera)	Gait	45 males and 45 females	2D estimated skeleton points with random forest
Present study	9-channels of EMG pressure and accelerometer sensors	Gait	12 males and 13 females	Recursive feature elimination based on gait feature set with SVM and RF classifiers

2.3. Importance of gait-subphase

The importance of classifying the gait sub-phases during walking has been the subject of several studies. Pappas et al. (2001) demonstrated a highly reliable gait phase detection system that can be used in gait analysis applications and can control the gait cycle of a neuroprosthesis used for walking. In addition to this application, the analysis of gait subphase can be used to control powered prosthestics and artificial legs (Hargrove, Simon, Lipschutz et al., 2013; Hargrove, Simon, Young et al., 2013; Ivanenko et al., 2013; Zhang & Huang, 2012) and tracking pedestrian position (Suh & Park, 2009), ambulatory rehabilitation systems (Rueterbories et al., 2010), and functional electrical stimulation assisted walking for subjects with a drop-foot walking condition (Pappas et al., 2001; Williamson & Andrews, 2000). Further, in the field of application of powered artificial prosthesis, the role of gait-subphase classification is crucial to control prosthesis for trans-femoral prosthesis patients, and many studies have been conducted for method of gait sub-classification using various sensors (Ryu & Kim, 2014, 2017; Ryu et al., 2016).

As mentioned above, since the analysis of walking characteristics based on gait sub-phases is important, we hypothesized that it is necessary to interpret gait characteristics by dividing the walking pattern differences based on gender in this paper.

2.4. The importance of feature selection

The EMG signal processing uses various neural network approaches such as convolutional neural networks (CNN) and long-short-term memory (LSTM) for EMG signal-based patterns recognition. However, CNNs are suitable for interpreting spatial correlations of multi-channel EMG signals but have the disadvantage of not being able to capture temporal information, and LSTM models excel at capturing temporal information of EMG signals, but extracting spatial information is difficult. Moreover, one of the reasons why feature selection is necessary in EMG signal processing is that many studies have concluded that the quality of features and the number of combinations of EMG signals have a meaningful impact on the performance of EMG-based pattern recognition (Boostani & Moradi, 2003; Khushaba et al., 2020; Phinyomark & Scheme, 2018; Scheme & Englehart, 2014). In particular, network-based EMG pattern recognition using raw signals is limited in that it cannot control single-channel EMG signals that contract or relax independently in multi-channel muscles. To resolve, determining optimal EMG features is an important factor contributing to reducing the effects of disturbances caused by electrodeposition shift, muscle fatigue, etc., and performance degradation caused by transient muscle contraction strength (Khushaba et al., 2020).

In many studies, information on gait has been analyzed based on various signals and feature extraction methods. For example, in studies based on EMG signals, gait characteristics may include four or more lower extremity muscle channels, including the quadriceps muscle of the thigh, and can be analyzed based on feature extraction methods in various time and frequency domains. When combining or selecting these many muscles and features, most studies have proposed a method of selecting the muscle with the highest recognition rate in the training data and the gait feature method with a significant difference on statistical analysis. Meng et al. (2010) used an arbitrary combination with features such as mean absolute value, waveform length, zero crossing, and slope sign changes to generate a hidden Markov model for gait phase recognition. Ziegier, Gattringer, and Mueller (2018) used only two kinds of features (weighted signal difference and root mean squared) for gait classification. Further, Ryu and Kim (2017), Ryu et al. (2016, 2019) determined the muscle and feature selection based on the highest recognition rate in the training data. However, these methods for feature selection may be arbitrary or empirical with respect to combining features; therefore, an automatic method of determining the optimal signal and feature more efficiently is required.

Feature selection approaches such as the filter method (Alonso-Atienza et al., 2013; Namsrai et al., 2013) and wrapper method (Llamedo & Martínez, 2010; Mar et al., 2011; Zhang et al., 2014) have been frequently used to reduce feature dimension and time complexity, and it can alleviate the problem of overfitting of the training model. The filter method has the fastest running time; however, it does not consider feature dependencies and tends to each feature separately when univariate techniques are used (Biswas, Bordoloi, & Purkayastha, 2016). The wrapper method has the advantages of better generalization and robust interaction with the classifier used for feature selection (Biswas et al., 2016).

In this study, we specifically used support vector machined-based recursive feature elimination (SVM-RFE) and random forest-based RFE (RF-RFE) for wrapper feature selection to select the optimal gait feature subset and reduce dimensionality. The RFE algorithm has powerful advantages of investigating and determining the optimal feature set by repeatedly removing irrelevant features, and it can determine the optimal feature subset and efficiency during an analysis of large complex biological data (Lin et al., 2018), and it has been proven to be more efficient than other feature selection methods (Guyon & Elisseeff, 2003; Park et al., 2018).

3. Database

3.1. Subjects

Thirty one healthy subjects (Koreans) were recruited to the study; however, six of the subjects were excluded post-analysis due to contact problems with the EMG sensors. Therefore, EMG data from 25 subjects, 12 males (mean age 24.3±1.44; height 174.7±4.88 cm; body mass 69.4±11.25 kg) and 13 females (mean age 23.6±2.33; height 163.2±5.66 cm; body mass 56.5±8.37 kg), were used for gait analysis as shown in Table 2. The subjects had no history of lower extremity or other musculoskeletal disorders, neurological pathology, orthopedic surgery, knee pain or pathology. Limb dominance was determined by skills such as kicking a ball or starting to walk. Twenty-one of the 25 subjects reported that they were right-limb dominant. The remaining subjects were left-limb dominant.

This study briefed each subject on the study's purpose, and the subjects provided written informed consent prior to participation in the experimental procedures. The study was approved by the Inha University Institutional Review Board (approval: 150603-1 A).

3.2. Instrumentation and data acquisition

A surface EMG signal was measured as MP150 and five BN-EMG2 units using a commercial device (BIOPAC Systems, Inc., CA, USA). Each BN-EMG2 unit acquires EMG signals from two channels, i.e., two muscles. Five BN-EMG2 units with 10 mm diameter adhesive electrodes was used as shown in Fig. 1 (Zygotebody & 3D Data Zygote Media Group, Inc. Online, 2020).

The EMG sampling rate was set to 1 kHz and it was sufficient to obtain EMG signals due to its frequency range of 0 to 500 Hz (Wang, Tang, & Bronlund, 2013). The nine muscles of the dominant limb selected for study were as follows: sartorius (SA), biceps femoris longus (BFL), rectus femoris (RF), gastrocneminus muscle (GM), tibialis anterior (TA), semitendinosus (SE), vastus lateralis (VL), vastus medialis (VM), and peroneus longus (PL). All adhesive electrodes were placed according to the guidelines of the International Society of Electrophysiology and Kinesiology. For obtaining kinematics data, we used an inertial measurement unit (IMU) sensor on the knee to measure the range of motion, and two pressure sensors on the sole to determine whether the heel and toe were touching the ground. Based on the pressure sensors, the gait sub-phases were classified into the following categories: initial-contact (IC), mid-stance (MS), pre-swing (PS), and swing (SW) based on the pressure sensors.

Subjects were asked to walk at a preferred, or comfortable speed across a 30 m walkway as shown in Fig. 2 and each subject walked a 250 steps. Fig. 3 shows a typical example of the quantitative data obtained.

3.3. Determination of reference gait phases

To investigate the gait characteristics in each gait phase, the pressure sensors were attached to the heel and toe of shoe insole of a 5 mm thick and generated the reference gait phases. The pressure sensors provided the four levels coded foot-switch signals of gait phases, initial contact, double supporting, pre-swing, and swing.

As shown in Fig. 4, the initial contact was defined as the pressure sensor of reference heel is on and the pressure sensor of reference toe is off, and then the foot-switch level become one. The double-supporting was started when all pressure sensors are onset, and the foot-switch level is two. The pre-swing was defined as the pressure sensor of reference heel is onset and the pressure sensor of reference toe is cessation, then foot-switch level become three. The swing was terminated when all pressure sensors are cessation, and the foot-switch level is four.

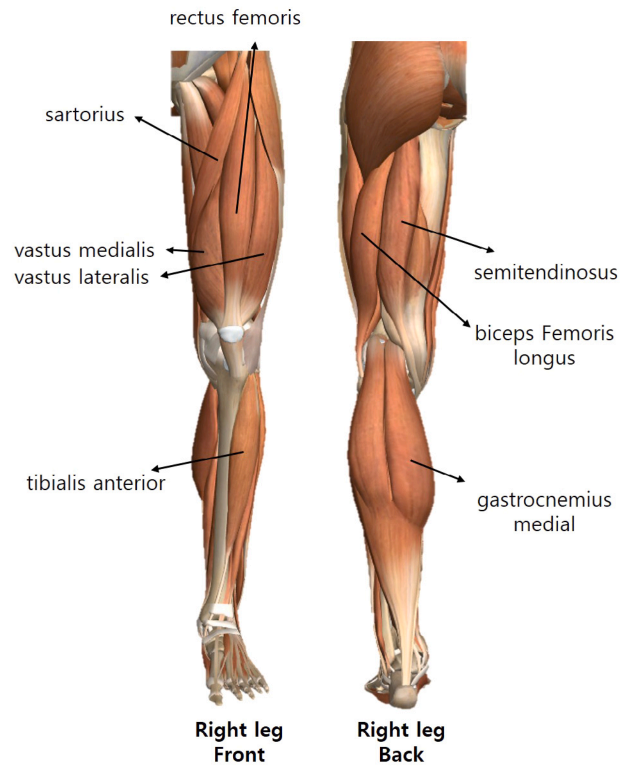

Fig. 1. Electromyographic (EMG) electrode position.

4. Materials and methods

4.1. Feature extraction

4.1.1. Anthropometric parameters

For obtaining the anthropometric parameters, data for age, height, weight, BMI, and leg length were obtained from all subjects. All the participants consented to anthropometric measurements and experiments by signing a consent form. BMI (k m^{-1}) was calculated from height and weight measurements and leg length was determined as the distance from the ground to the center of the hip joint.

4.1.2. Temporal and kinematics parameters

Temporal parameters consist of gait duration (ms) and gait cycle (%) parameters. Each phase of the gait was calculated by the duration of the corresponding gait phase as a percentage of the total gait duration. Kinematic parameters have two kinds of parameters as a joint angle range of motion (degrees) and a root mean squared (RMS) acceleration (m/s^2). As shown in Fig. 2, the knee angle and acceleration are extracted through the IMU sensor attached to the knee.

4.1.3. Muscle activation parameters

Twenty five features were extracted using EMG signals for gait characteristic in time- and frequency domain as shown in Table 3 (Phinyomark, Phukpattaranont, & Limsakul, 2012). The features in time domain has the advantage of low time complexity and fast calculation because these features do not need any transformation (Hudgins, Parker, & Scott, 1993; Oskoei & Hu, 2008; Tkach, Huang, & Kuiken, 2010). In this study, seven-teen feature methods in time domain were used as following: integrated EMG (IEMG), mean absolute value (MAV), simple square integral (SSI), variance of EMG (VAR), root mean square (RMS), log detector (LOG), waveform length (WL), average amplitude change (AAC), difference absolute standard deviation value (DASDV), amplitude of the first burst (AFB), zero crossing (ZC), Willison amplitude (WAMP), slope sign change (SSC), mean absolute value slope

Table 2
Demographics on age, height, weight, and BMI obtained for subjects.

	Male (n = 12)	Female (n = 13)	p
	Mean (SD)	Mean (SD)	
Age (*years*)	24.3 (1.44)	23.6 (2.33)	0.360
Height (cm)	174.7 (4.88)	163.2 (5.66)	<0.001**
Weight (kg)	69.4 (11.25)	56.5 (8.37)	0.004*
BMI (kg m^{-1})	22.7 (3.23)	21.1 (2.40)	0.185
Leg length (cm)	98.8 (3.65)	89.8 (2.97)	<0.001**
ANCOVA F value	0.76 (d.f. = 1)		0.394

Note: SD means the standard deviation; Statistical analysis methods were used the independent t-tests and ANCOVA (Analysis of covariance); ANCOVA tests were done with height as the covariate, and gender as the fixed factor; d.f. means the degree of freedom. The asterisk (*) indicates statistical significance at $p < 0.05$ and asterisks (**) indicates statistical significance at $p < 0.001$.

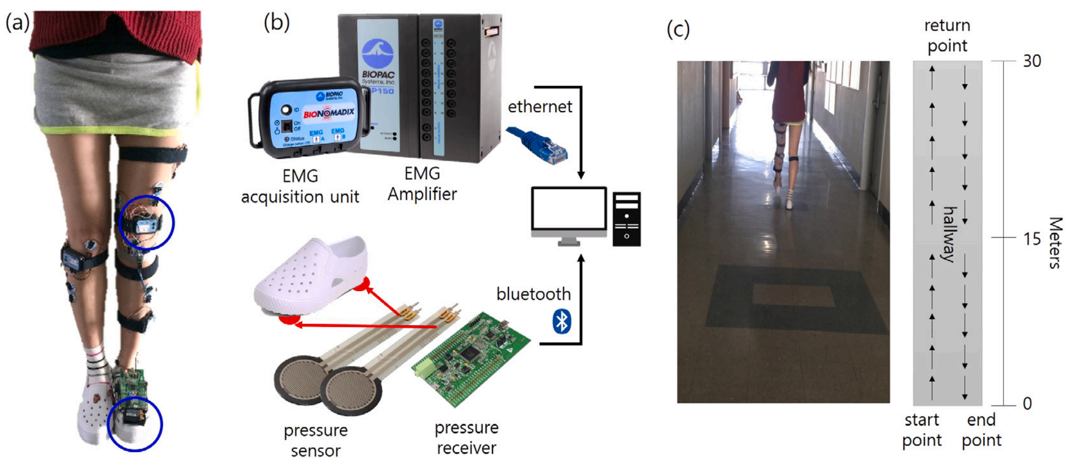

Fig. 2. Experimental environment: (a) Instrumented participant (b) gait sub-phase detection using the pressure sensors (c) gait environment of the hallway walked by the recruited subjects during the experiment.

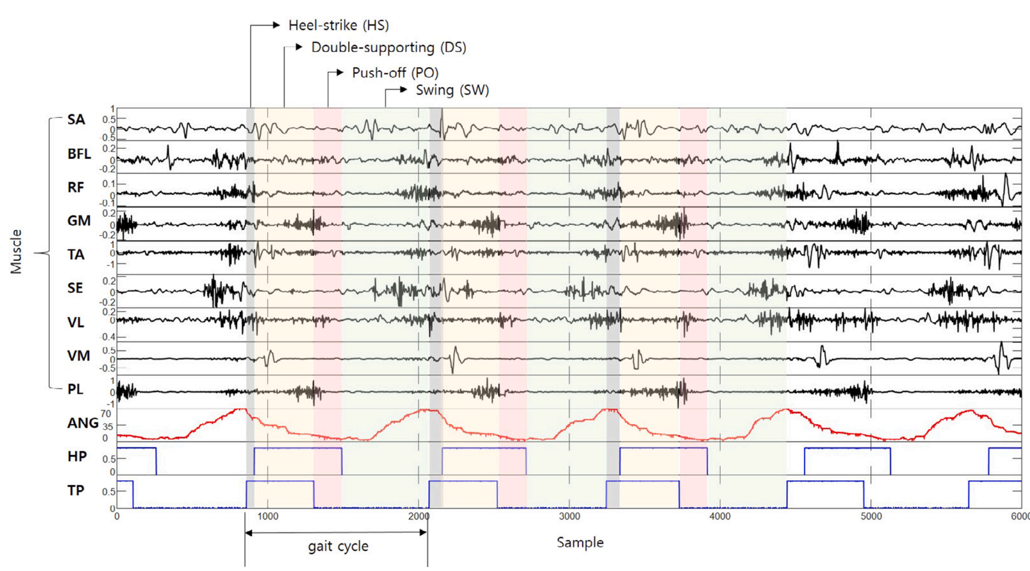

Fig. 3. Example of the quantitative electromyography data (SA: Sartorius; BFL: biceps femoris longus; RF: rectus femoris, GM: gastrocneminus muscle, TA: tibialis anterior, SE: semitendinosus, VL: vastus lateralis, VM: vastus medialis, and PL: peroneus longus), knee angle (ANG: angle [degree]), and pressure data (HP: heel pressure; TP: toe pressure).

(MAVSLP), histogram of EMG (HIST), auto-regressive coefficients (AR), and cepstral coefficients (CC).

The features in frequency domain are usually used to analyze the fatigue of the muscle and motor unit recruitment (Phinyomark et al., 2012). We extracted eight parameters in frequency-domain as following: mean frequency (MNF), median frequency (MDF), peak frequency (PKF), mean power (MNP), total power (TTP), the second spectral moment (SM2), the third spectral moment (SM3), and frequency ratio (FR).

Twenty-five features were generated from nine muscle channels and 250 steps per subject, resulting in a total of 56,250 feature vectors. A total of 656,250 parameters are obtained from twenty-five subjects.

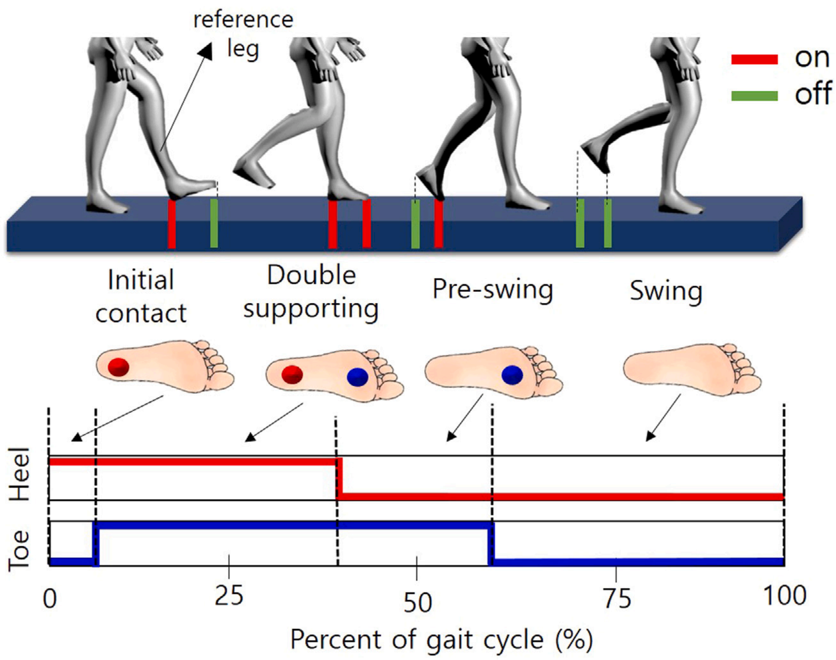

Fig. 4. Determination of four gait phases using foot pressure sensors.

Table 3
Summary of gait feature.

	Parameters		Description
Time-domain	1	IEMG	The summation of absolute values of the EMG signal amplitude
	2	MAV	The average of absolute value of the EMG signal amplitude
	3	SSI	The summation of square values of the EMG signal amplitude
	4	VAR	The average of square values of the deviation of that variable
	5	RMS	Root mean square
	6	LOG	Log detector that estimate of the muscle contraction force
	7	WL	Cumulative length of the EMG waveform over the time segment
	8	AAC	Average amplitude change
	9	DASDV	Difference absolute standard deviation value
	10	AFB	Amplitude of the first burst
	11	ZC	Number of times that amplitude values of the EMG signal cross zero amplitude level
	12	WAMP	Number of times that difference between the EMG amplitude among two adjoining segments that exceeds a threshold
	13	SSC	Number of times that slope of the EMG signal changes sign
	14	MAVSLP	Mean absolute value slope
	15	HIST	Histogram of EMG
	16	AR	Auto-regressive
	17	CC	Cepstral coefficients
Frequency-domain	18	MNF	Average frequency as sum of product of the power spectrum and the frequency divided by sum of the spectrum intensity
	19	MDF	Frequency at which the spectrum is divided into two regions with equal amplitude
	20	PKF	Frequency at which the maximum power occurs
	21	MNP	Average power of the EMG power spectrum
	22	TTP	An aggregate of the EMG power spectrum
	23	SM2	Spectral moment is an alternative statistical analysis from the EMG power spectrum with second moment
	24	SM3	Spectral moment is an alternative statistical analysis from the EMG power spectrum with third moment
	25	FR	Ratio between the low frequency components and the high frequency components of the EMG signal

4.2. Feature selection

The role of feature selection method is to reduce the time- and space-complexity of learning algorithm. Although this study was not conducted in a real-time environment, feature selection was crucial because it can be applied to various fields, such as medical systems, robotics, and biometric applications in future studies while considering time complexity. In particular, for a powered prosthesis used to classify the gait sub-phases, time complexity should be considered to obtain the results of gait classification without a delay in real time. In this study, two kinds of recursive feature elimination methods were used as SVM-RFE and RF-RFE. As shown in Fig. 5, the models of SVM-RFE and RF-RFE use the same end-to-end architecture with various parameters such as temporal, kinematics, EMG parameters extracted.

4.2.1. SVM-RFE

Support vector machine based on recursive feature elimination (SVM-RFE) method was proposed by Guyon et al. (2002) to implement gene selection for cancer classification. SVM-RFE has the linear kernel and provide the ranked best feature subset by iteratively eliminating an unnecessary feature. The result of method applying SVM-RFE will probably have good performance (Yan & Zhang, 2015) because SVM-RFE generate a ranking criterion based on the weights of the features that properly classify the classes.

The SVM finds a separating hyperplane with the largest margin, we trained SVM using the training dataset k-fold cross-validation to validate trained SVM models. Given a set of training samples $\{\mathbf{x}_i, y_i\}$, $x_i \in R^d$, $y_i \in \{1, 1\}$, $i = 1, \ldots, n$, the decision function $f(t)$ of each SVM

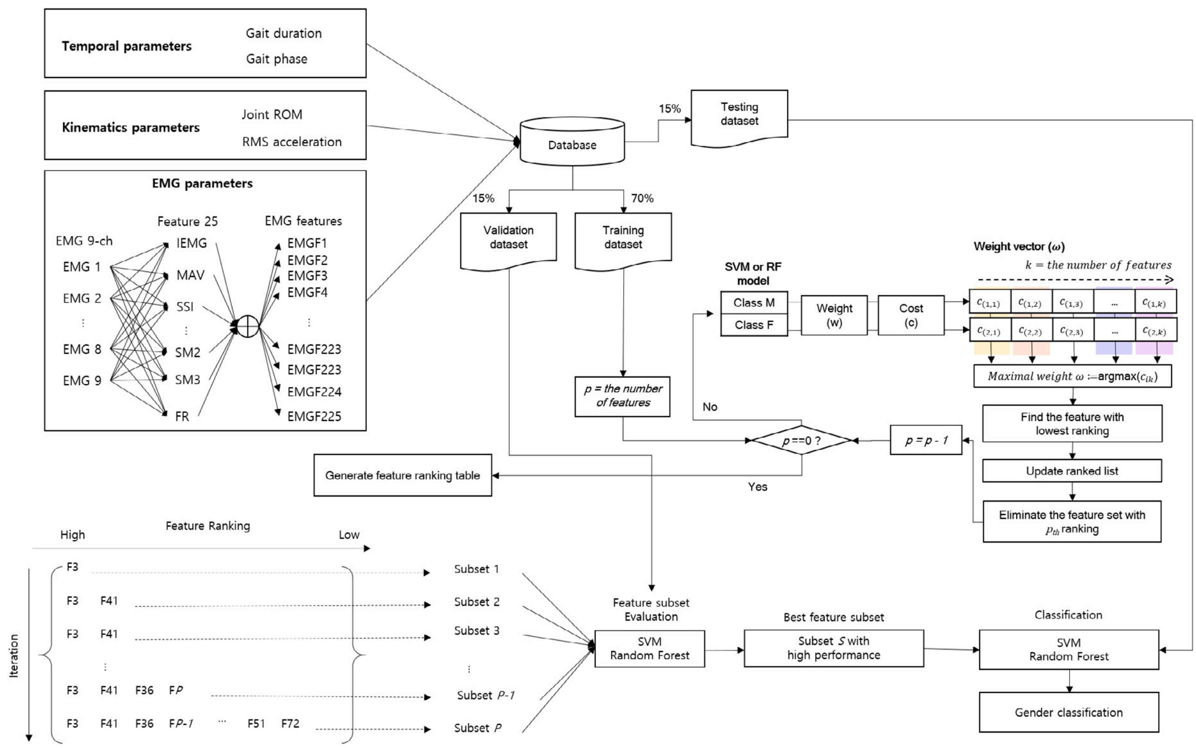

Fig. 5. Proposed gender classification method based on recursive feature elimination.

can be obtained using formula (1).

$$f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + b. \tag{1}$$

where the weight vector is $w = [w_1, w_2, \ldots, w_m]^T$ and b denotes bias. The dual form of the Lagrangian formulation of the problem can be written by using formula (2).

$$\begin{aligned} L_D &= \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=0}^{n} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j \\ &\quad subject\ to \sum_{i=1}^{n} \alpha_i y_i \\ &\quad \alpha_i \geq 0 \end{aligned} \tag{2}$$

where α_i are the Lagrange multipliers. Then the weight w of each SVM can be calculated by using formula (3).

$$\mathbf{w} = \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i. \tag{3}$$

where α_i is the Lagrange multipliers involved in maximizing the margin of the classes. The ranking criterion RC_k for k feature can be computed as $(w_k)^2$, and the kth feature with the smallest value RK_{small} among RK is eliminated by using formula (4).

$$RK_{small} = argmin_k((w_k)^2). \tag{4}$$

The feature with the smallest ranking score was eliminated, and the SVM was retrained using the remaining feature set except for RK_{small}. These steps were performed iteratively until one feature (a single feature with the highest ranking score) remained.

4.2.2. RF-RFE

Random forest (RF) is a powerful classifier because it can perform effectively and efficiently with advantages such as unbiased estimator and easy to parallel (Chen et al., 2018). The training dataset was generated by randomly drawing with n_{tree} bootstrap samples from the original data using bagging (bootstrap aggregating). Input data was predicted by aggregating the predictions of the n_{tree} trees and the error rate can be obtained. At each bootstrap iteration, about 36% of the total data is not included in the bootstrap sample and is randomly extracted (out-of-bag, or OOB) to evaluate the performance of the built model (Liaw et al., 2002).

For training the RF-RFE, the importance of feature f_i in the random forest (Ma et al., 2016; Sun et al., 2018) using formula (5).

$$f_i imp = \frac{1}{N} \sum_{i=1}^{N} (O_i - T_i^f) \tag{5}$$

where O_i and f are OOB error and features, respectively. Based on the OOB data, OOB error O_i of each decision tree in the random forest was obtained and then noise interference is randomly added. Finally, the OOB error from new training set is calculated as T_i^f.

The importance of feature f_i with the smallest ranking score was eliminated, and the RF-RFE was retrained using the remaining feature set except for RK_{small} (RK_{small} described in Section 4.2.1. SVM-RFE). The feature elimination process iteratively until a final ranking (a single feature with the highest ranking score) constructed.

4.3. Training the models

As shown in Table 4, the various models were trained considering the five scenarios to improve the performance of the proposed method. In scenario I, II, and III, all three types of models were trained using SVM and RF classifier from various parameters extracted without feature selection method. The parameters were extracted in each gait cycle (100%), i.e. without classification of gait-subphase.

For scenario I, the model was trained using temporal and kinematic parameters in one cycle. The number of parameters in each gait was three (one temporal parameter (gait duration (ms)) and two kinematics parameters (joint angle range of motion and RMS acceleration)) and total was 750 (250 gait steps x 3 parameters, one person). The model of scenario II used EMG parameters and the number of parameters in each gait was 225 (25 EMG parameters x 9 EMG channels) and total was 56,250 (250 gait steps x 225 EMG parameters, one person). For scenario III, the model was trained using one temporal, two kinematic,

Table 4
Description of five scenarios designed in the proposed method.

	Parameter Information	Independence of gait subphase	# Total features (one person)	# Final features (one person)
Scenario I	Temporal, Kinematic parameters	No	3	3
Scenario II	All EMG parameters (Channel with features)	No	225	225
Scenario III	All parameters (Temporal, Kinematic, EMG)	No	229	229
Scenario IV	Selected temporal, kinematic, EMG parameters	No	229	Depending on the performance of feature selection
Scenario V	Selected temporal, kinematic, EMG parameters	Yes	912	Depending on the performance of feature selection

Note: In Scenario I, II, III, and IV, the parameter as gait cycle (%) was excluded because the gait cycle is 100% unless the gait subphase is classified. Above mentioned the number of features were calculated by individual. Each subject performs 250 steps.

and 225 EMG parameters and total of parameters was 57,000 (250 gait steps x 228 parameters, one person). In scenario I and II, the parameter as gait cycle (%) was excluded because the value of gait cycle is 100% unless the gait subphase is classified.

The models of scenario IV and V use the same end-to-end architecture with feature selection method, but there was difference in the independence of the gait subphase. We trained only model in scenario V using parameters that separated the gait subphase to investigate the function and importance of independence of the gait subphase. For scenario IV, the model was trained from total 228 feature data (but the number of final selected feature is depending on the performance of feature selection model) with each SVM-RFE or RF-RFE. The model in scenario V used total 912 feature data (but the number of final selected feature is depending on the performance of feature selection model) with SVM-RFE or RF-RFE for training. Finally models in scenario IV and V trained were evaluated using SVM and RF from test data.

4.4. Performance evaluation method

4.4.1. Statistical analysis

To analyze the relationship between gait parameters among females and males, two statistical methods were used: a two sample t-test and an analysis of covariance (ANCOVA) test. The ANCOVA test was performed with height as the covariate and gender as the fixed factor in order to account for the anthropometric and temporal parameters. Statistical analyses were performed using MATLAB 2019 software. The significance level was set at α= 0.05. An asterisk (*) indicates statistical significance at $p < 0.05$, and two asterisks (**) indicate statistical significance at $p < 0.001$.

4.5. Classification performance measures

We used six performance measures, sensitivity (recall), specificity, precision, F1 score, average accuracy, and error rate, for validation of the proposed method to classify the gender. These measures can be calculated using formulas (6) to (10) (Kiranyaz, Ince, & Gabbouj, 2015). To calculate these measures, the number of true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) results were counted for each record.

$$Sensitivity\ (Recall) = TP/(TP + FN) \times 100 \tag{6}$$

$$Specificity = TN/(TN + FP) \times 100 \tag{7}$$

$$Precision = TP/(TP + FP) \tag{8}$$

$$F1\ score\ = 2 \times (Precision \times Recall)/(Precision + Recall) \tag{9}$$

$$Average\ accuracy = (TP + TN)/(TP + TN + FP + FN) \times 100 \tag{10}$$

$$\begin{aligned} &Error\ rate = \tfrac{1}{N}\sum_{i=1}^{n} I, \\ &I = \begin{pmatrix} if\ y_i == \hat{y}i, 0 \\ other,\ 1 \end{pmatrix} \end{aligned} \tag{11}$$

where y_i and $\hat{y}i$ denote the true class and the predicted class.

5. Results

To compare gait characteristics in the female and male groups, the anthropometric parameters, temporal parameters, knee kinematics, and limb muscle activation were analyzed. Further, we designed five kinds of models to investigate the robust method for gender classification as Table 4.

5.1. Statistical analysis

5.1.1. Anthropometric parameters

As shown in Table 2, the mean age of the male (M=24.3, SD=1.44) and female (M=23.6, SD=2.33) group was not significantly different (t=3.27, p=0.360). Female physique was smaller than that of the males in terms of height (t=3.27, p<0.001), weight (t=3.27, p=0.004), and leg length (t=3.27, p<0.001). The BMI of the male (M=22.7, SD=3.23) and female (M=21.1, SD=2.40) group was not significantly different (t=3.27, p=0.185), but the BMI of female group was lower than that of male group. However, ANCOVA, using height as the covariate of the male and female group, showed no significant difference (ANCOVA, F=0.76, degree of freedom (d.f.)=1, p=0.394).

5.1.2. Temporal parameters

Temporal parameters were analyzed with respect to the gait subphases (Table 5). In the female group, the duration of MS, PS, and SW phase were smaller than that in the male group ($p < 0.05$), but the duration of IC was larger and significantly different (t=3.27, p=0.010). The ANCOVA, using height as the covariate, showed that the duration of the gait sub-phases may be a gender feature.

The gait sub-phase cycles (%) of the IC, MS, and SW phases were significantly different. In the IC phase, the gait cycle of the male group (M=10.68, SD=6.72) was smaller than that of the female group (M=12.16, SD=6.97). In addition, the gait cycle of the male group (M=13.63, SD=4.01) was smaller than that of the female group (M=13.70, SD=4.58) in the PS phase.

5.1.3. Kinematics

Table 6 shows the statistical result of the kinematics parameters. The averages of the knee angle range of motion in the female group were smaller than those in the male group in the MS (t=3.51, $p < 0.01$), PS (t=2.75, p=0.013), and SW phases (t=0.89, p=0.151). The knee angle ROM in the IC was not significantly different between the two groups (t=1.96, p=0.062). However, the knee angle ROM of women (M=22.19, SD=1.05) was slightly lower than that of men (M=23.14, SD=2.04). Statistical analysis of the root-mean-square (RMS) acceleration indicated that there were significant differences in IC (t=4.96, p<0.01), MS (t=-4.73, p<0.01), PS (t=-2.93, p=0.003), and SW (t=13.08, p<0.01) phases between the male and female groups.

Table 5
Temporal parameter.

	Male (n = 12)	Female (n = 13)	p
	Mean (SD)	Mean (SD)	
IC: Initial contact (ms)	137.94 (150.74)	147.95 (156.95)	0.010*
ANCOVA F value	73.73 (d.f. = 1)		<0.001**
MS: mid-stance (ms)	394.96 (87.99)	363.30 (130.21)	<0.001**
ANCOVA F value	15.74 (d.f. = 1)		<0.001**
PS: Pre-swing (ms)	172.99 (54.50)	163.89 (61.50)	<0.001**
ANCOVA F value	49.29 (d.f. = 1)		<0.001**
SW: Swing (ms)	565.46 (71.47)	530.35 (99.38)	<0.001**
ANCOVA F value	36.36 (d.f. = 1)		<0.001**
IC: Initial contact phase (% of gait cycle)	10.68 (6.72)	12.16 (6.97)	<0.001**
ANCOVA F value	12.86 (d.f. = 1)		<0.001**
MS: mid-stance phase (% of gait cycle)	31.16 (6.47)	29.93 (8.14)	<0.001**
ANCOVA F value	11.91 (d.f. = 1)		<0.001**
PS: Pre-swing (% of gait cycle)	13.63 (4.01)	13.70 (4.58)	0.616
ANCOVA F value	6.56 (d.f. = 1)		<0.001**
SW: Swing (% of gait cycle)	44.54 (3.80)	44.21 (4.04)	<0.001**
ANCOVA F value	9.21 (d.f. = 1)		<0.001**

Note: SD refers to the standard deviation; Statistical analysis methods: independent t-tests and ANCOVA (Analysis of covariance); ANCOVA tests were done with height as the covariate, and gender as the fixed factor; d.f. means degree of freedom. The asterisk (*) indicates statistical significance at $p < 0.05$ and asterisks (**) indicates statistical significance at $p < 0.001$.

Table 6
Kinematics parameters.

	Gait sub-phase	Male (n = 12)	Female (n = 13)	p
		Mean (SD)	Mean (SD)	
Joint angle range of motion ($degrees$)				
Knee	IC: Initial contact	23.14 (2.04)	22.19 (1.05)	0.062
	MS: mid-stance	24.20 (3.51)	21.15 (2.27)	<0.001**
	PS: Pre-swing	39.09 (2.90)	37.11 (5.10)	0.013*
	SW: Swing	66.86 (3.47)	65.15 (5.24)	0.015*
RMS acceleration (m/s^2)				
Knee	IC: Initial contact	2.16 (0.05)	2.09 (0.08)	<0.001**
	MS: mid-stance	1.96 (0.04)	1.97 (0.06)	<0.001**
	PS: Pre-swing	1.88 (0.04)	1.88 (0.06)	0.003*
	SW: Swing	1.98 (0.05)	1.96 (0.06)	<0.001**

Note: SD refers to the standard deviation; Statistical analysis methods were used for the independent t-tests. The asterisk (*) indicates statistical significance at $p < 0.05$ and asterisks (**) indicates statistical significance at $p < 0.001$.

5.1.4. Muscle activation

Muscle activation was also found to be strongly affected by gender (Fig. 6 and 7). Most muscle activations recorded on the 9-channels of EMG in the female group were larger than those in the male group with respect to the gait sub-phases. In the IC phase, the muscle activation of other muscles except the tibialis anterior (t=0.280, p=0.977) was larger in the female group than in the male group, and there were significant differences between the female and male groups (p<0.01). In the PS phase, activation of other muscles except the rectus femoris (t=1.789, p=0.073) was larger in the female group than in the male group, and there were significant differences between the female and male groups (biceps femoris longus: p<0.05, others: p<0.01). Activation of all muscles in females was larger than that of males and there was a significant difference between the two groups (p<0.01) in both the MS and SW phases.

5.2. Performance for gender classification

5.2.1. Effect of feature selection

To validate the proposed models using feature selection method, the mean of error rates of models in scenario IV and V were calculated from the validation data (15% of the total data) and test data (15% of the total data) with k-fold cross validation (k=5) as shown in Fig. 8. In scenario IV (top figure of Fig. 8), the best error rates of SR-SVM (SVM-RFE with SVM classifier), RR-SVM (Random forest-RFE with SVM classifier), SR-RF (SVM-RFE with random forest classifier), and RR-RF (RF-RFE with random forest classifier) were 0.0705 ± 0.167 (feature set dimension=189), 0.0255 ± 0.089 (feature set dimension=76), 0.031 ± 0.118 (feature set dimension=68), and 0.0156 ± 0.059 (feature set dimension=51), respectively.

For scenario V, the best error rates of SR-SVM, RR-SVM, SR-RF, and RR-RF were 0.0198 ± 0.0223 (feature set dimension=182), 0.025 ± 0.0123 (feature set dimension=91), 0.0131 ± 0.0108 (feature set dimension=71), and 0.0255 ± 0.0135 (feature set dimension=88), respectively.

We measured performance using test data based on the model with the lowest error rate among the models evaluated with validation data.

5.2.2. Performances of different models

Table 7 shows the classification results of gender classification. The scenario V using SVM-RFE with random forest classifier had the best performance (sensitivity: 99.11%, specificity: 99.11%, and average accuracy: 99.11%). This model trained by using SVM-RFE and selected 71 features. Although the sensitivity of the model in scenario V using RF-RFE with SVM classifier was higher than that of the model in scenario V using SVM-RFE with random forest classifier, but not average accuracy and specificity.

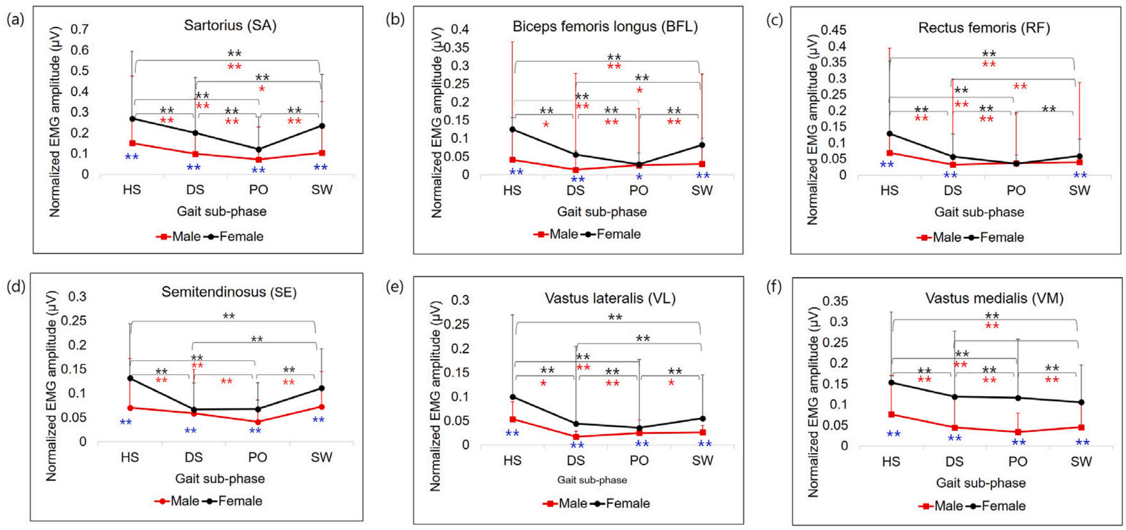

Fig. 6. Comparison of activation of the thigh muscles (SA, BFL, RF, SE, VL, and VM) in the female and male groups. In the gray-bracket, the upper black asterisks indicate comparisons in the female group and the lower red asterisks indicate comparisons in the male group. The blue asterisks represent the results of the t-test performed between the male and female groups. The asterisk (*) indicates statistical significance at $p < 0.05$, and the two asterisks (**) indicate statistical significance at $p < 0.001$.

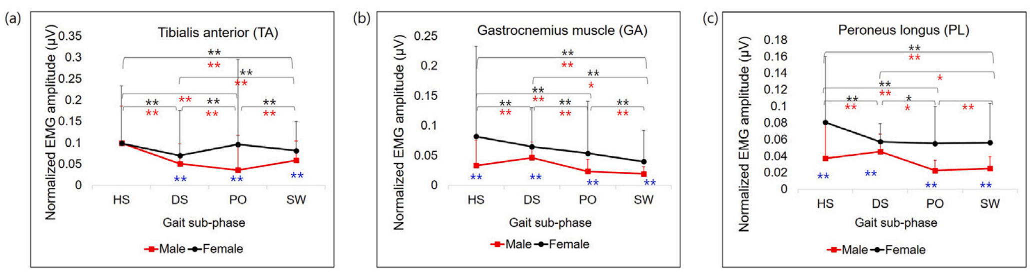

Fig. 7. Comparison of the activation of calf muscles (TA, GA, and PL) in the female and male groups. In the gray-bracket, the upper black asterisks indicate comparisons in the female group and the lower red asterisks indicate comparisons in the male group. The blue asterisks represent the results of the t-test performed between the male and female groups. The asterisk (*) indicates statistical significance at $p < 0.05$, and the two asterisks (**) indicate statistical significance at $p < 0.001$.

Table 7
Gender classification performances in Scenario I to V.

	# Features	Feature selection	Classifier	Sensitivity (%)	Specificity (%)	Average Accuracy (%)
Scenario I	3		SVM	46.72	46.12	46.44
	3		Random forest	53.00	53.23	53.11
Scenario II	225		SVM	81.07	73.87	77.00
	225		Random forest	77.02	72.51	74.56
Scenario III	229		SVM	87.77	90.55	89.11
	229		Random forest	92.00	92.00	92.00
Scenario IV	189	SVM-RFE	SVM	94.30	95.50	94.89
	76	SVM-RFE	Random forest	96.04	96.86	96.44
	68	RF-RFE	SVM	96.90	97.32	97.11
	51	RF-RFE	Random forest	96.27	97.51	96.88
Scenario V	182	SVM-RFE	SVM	98.22	98.22	98.22
	71	SVM-RFE	Random forest	99.11	99.11	99.11
	91	RF-RFE	SVM	99.55	98.25	98.89
	88	RF-RFE	Random forest	98.89	98.89	98.89

Table 8 represents the confusion table for the model based on SVM-RFE with random forest classifier in scenario V with highest performance. Total of test data is nine-hundred because testing data was extracted 15% (6,000 total data x 15% = 900) from the total data (each group has 3,000 data (N=12, 250 steps)). The recall, precision, and F1 score of that model were 0.99, 0.99, and 0.99, respectively. The final accuracy was 99.11%.

6. Discussion

6.1. Interpretation of results

The goal of this study was to compare the anthropometric and temporal parameters, knee kinematics, and muscle activation in the gait sub-phases during walking between males and females. Many

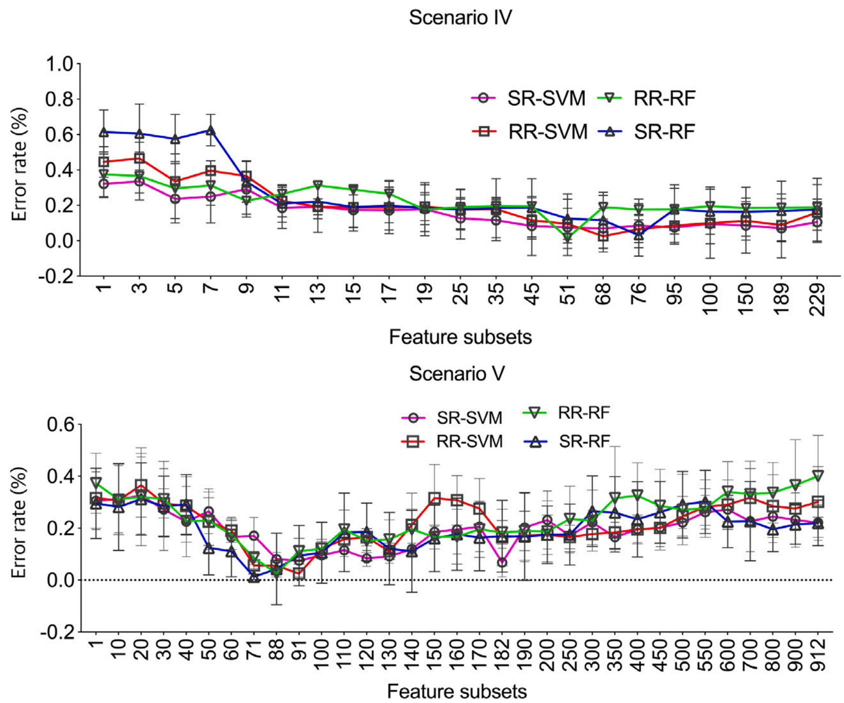

Fig. 8. Error rate for the validation data. The top panel shows Model I (EMG signal). The bottom panel corresponds to Model II (temporal, kinematics, and EMG signal). In the legend, SR stands for support vector machine-based recursive feature elimination, RR stands for random forest-based recursive feature elimination, SVM stands for support vector machine classifier, and RF stands for random forest classifier.

Table 8
Confusion table for SVM-RFE with Random forest classifier in Scenario V.

		Hypothesized class		
		Male	Female	Total
Ground Truth	Male	446	4	450
	Female	4	446	450
	Total	450	450	900

Note: Total of test data is nine-hundred. Training, validation, and testing data were extracted 70%, 15%, and 15%, respectively, from the total data.

researches have studied to the gender-based differences during gait walking (Chiu & Wang, 2007; Chumanov et al., 2008; Chung & Wang, 2010). These studies have provided significant information in the medical and rehabilitation fields, but most of them have the limitation of including a small number of gait steps for each subject. It is important to collect sufficient data because insufficient amounts of data can interfere with the quantification assessment of natural variability associated with muscle activity during free walking (Di Nardo et al., 2015). In a study by Chung and Wang (2010), each subject performed the walk for 10 trials of ground reaction force assessment. In a study by Chumanov et al. (2008), the gait assessment procedure was performed with five strides for each condition and each subject. In a natural walking environment, Chiu and Wang (2007) asked each subject to walk on a walkway for 10 steps. However, since there is still no consensus on whether gender-based differences exist in gait characteristics, our study attempted to support the results of these studies containing gait analysis, aiming to collect more gait data than previous studies.

In Table 2, the anthropometric parameters including height, weight, and leg length of females were significantly smaller (p<0.01). The BMI of females was smaller than that of males, but this did not significantly affect the above parameters since BMI was calculated using only body weight and height.

The leg length of the females was shorter than that of the males, and a significant difference was found between the two groups (p<0.05). However, the ANCOVA analysis, using height as the covariate and gender as the fixed factor, was not a significant parameter to prove a difference between the two groups. Our results are consistent with that of previous studies (Cho et al., 2004). Cho et al. (2004) demonstrated that the physique of females was smaller than that of males, but was not one of the gender features of gait.

In Table 5, the parameters of stride time (ms) and gait cycle (%) in gait sub-phases (IC, MS, and SW), except for PS phase, were significantly different between females and males. However, most studies support this result that stride time (%) does not have a gender-based significant difference (Auvinet et al., 2002; Cho et al., 2004; Kadaba et al., 1990; Ryu et al., 2006). Studies by us and others (Cho et al., 2004; Ryu et al., 2006), including Koreans participants, show that the stance time (%) of females was higher than that of males, and the swing time (%) of females was comparatively lower. The ANCOVA, using height as a covariate, was performed to increase the reliability of the result. The stride time parameters of all gait sub-phases (IC, MS, PS, and SW) showed significant differences. Therefore, since the stride time parameters are affected by height (covariate), it is evident that this parameter is not important to identify gender-based differences.

As can be seen in Table 6, females had both a lower angle and RMS acceleration (m/s^2) of the knee joint than males, and our results provide clear evidence of gender-based differences in the angle and RMS acceleration of the knee joint. This is consistent with the hypotheses that ROM of females is lower than that of males. Several studies have addressed the gender-based differences in ROM of the knee joint during walking. Bruening et al. (2015) found that the angles in ROM of the knee were 67.2 and 68.1 degrees in females and males, respectively. Furthermore, Cho et al. (2004) found that females have less landing impact on the ground at the heel-strike and less contraction of the knee joint. Our results were analyzed for the various gait sub-phases. The knee joint angle of females was lower than that of males in all gait sub-phases and our study demonstrated that there were significant differences between the two groups for MS, PS, and SW, but not IC.

With respect to muscle activation between the two groups during walking, the females had significantly higher muscle activity in most muscles than the males in this study. When comparing the results of the

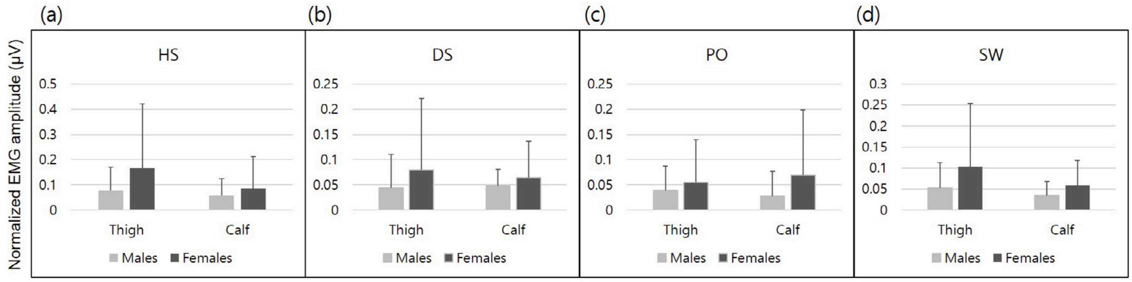

Fig. 9. Comparisons of muscle activation between the thigh (SA, BFL, RF, SE, VL, and VM) and calf (TA, GA, and PL) muscles in the female and male groups: (a) initial contact (IC) (b) mid-stance (MS) (c) pre-swing (PS) (d) swing (SW). The asterisks indicate the results of the t-test statistical analysis between the male and female groups. The asterisk (*) indicates statistical significance at $p < 0.05$ and asterisks (**) indicates statistical significance at $p < 0.001$.

Table 9
Gender classification accuracy of the proposed and existing approaches.

Publication	Data type	Method	Accuracy
Mansanet, Albiol, and Paredes (2016)	2D image	Local feature with deep neural networks	96.25
Cabra, Mendez, and Trujillo (2018)	ECG signal	Fiducial feature with KNN classifier	95.1
Dong et al. (2020)	Accelerometer and gyroscope	Motion data with random forest	98.7
Dogan and Oztaysi (2019)	Beacon data (users path)	Levenshtein-based Fuzzy KNN	88.9
Jain and Kanhangad (2018)	Accelerometer and gyroscope	Feature level combination with bagging	94.4
Present study	Temporal, kinematics, EMG parameters	SVM-RFE with random forest	99.1

thigh and calf muscles (Fig. 9), the normalized EMG amplitude value for the female group was higher than that of the male group for each gait sub-phase. The statistical results for the muscle activation pattern support the findings of previous studies. Chiu and Wang (2007) reported that females showed significantly higher tibialis anterior muscle activity, ankle motion, and vertical ground reaction force as compared to males. Though not in straight walking, Sigward and Powers (2006) reported that females had higher muscle activation of the quadriceps, medial hamstring, and lateral hamstring during side-step cutting as compared to males.

The muscle activation of the lower limb varies in its magnitude, frequency, and duration with respect to gait cycle (Di Nardo et al., 2015; Howard, 2016). In our study, as shown in Figs. 6 and 7, although the muscle activation between male and female group showed significant differences in almost muscle channels, there are larger difference between two groups in the muscles that are activated at each gait phase.

In the quadriceps of the thigh muscles, BFL, RF, VL, and VM muscles, these four muscles are mostly activated in the IC and SW phases. As shown in Fig. 3, the difference in muscle activity between male and female groups is mostly large in IC and SW. In calf, the muscle GA is typically activated in gait phases as IC and MS, the muscle TA is activated in PS and SW. As shown in Fig. 7 the result showed that the difference in muscle activation between the two groups was greater in the corresponding gait phase, which is activated than in other gait phases.

In particular, our findings showed that the variation of muscle activation of female group increases or decreases more rapidly than male group. This finding reported with the significantly higher ankle joint detected in females, compared to males (Di Nardo et al., 2015; Howard, 2016).

6.2. Effect of gait sub-phases

Fig. 8 shows the performance evaluation when the gait phase was classified (scenario IV) and when the entire gait cycle was considered (scenario V). It is clear that the proposed scenario V showed more robust performance than scenario IV, but additional sensors such as a foot-switch sensor or an angle sensor that can determine sub-phases are required for gait sub-phase determination. However, since these sensors play an important role in powered prosthetics or walking robots, the findings of this study can be used to conclude that the classification of gait phases may be effective in applications requiring robust performance.

6.3. Comparisons of with the state-of-the-art

Table 9 shows the comparison of gender classification performances of the proposed and existing approaches. Mansanet et al. (2016) proposed the local feature with deep neural networks using 2D images for gender classification, and the result showed at 96.25%. Dong et al. (2020) used accelerometer and gyroscope data and archived the classification performance of 98.7%. Although it is hard to compare the performances of the studies in Table 9 with the proposed method since there were several differences in the sensor's types and database, but each study has a crucial contribution depending on the field where it is used and utilized. However, the method proposed in this study supports a system that automatically finds and provides the optimal features with the highest ranking among the various signals and many features in the training stage. The approach of selecting several empirical and arbitrary features with a high recognition rate may include the challenge of a repeat statistical analysis in case there are changes in targets, such as the dataset, feature extraction methods, or signal used. Therefore, based on our study, we conclude that an effective system can be achieved by extracting more gait information and determining the optimal feature combination.

7. Conclusion

In this paper, we have presented an approach for gender classification in normal walking. This study has two aspects as a result of statistical analysis and classification using machine learning. For statistical analysis result, the results of our study indicate that gender-based differences have a significant influence on kinematic and muscle activity measurements. This study have focused on gender-based differences with respect to gait characteristics, by analyzing gait sub-phases during normal walking.

The temporal parameters of stride time (ms) and gait cycle (%) in gait sub-phases such as initial contact, mid-stance, and swing were significantly different between females and males (p<0.01). With respect to kinematic parameters, females exhibited both a lower angle and RMS acceleration (m/s^2) of the knee joint as compared to males, and our results show that there is clear evidence of gender-based differences in knee angle movement. Further, muscle activation in the female group was larger than that in the male group with respect to the gait sub-phases, and these differences were statistically significant.

For classification performance, the proposed gender classification method showed the powerful performance of 99.11% using SVM-RFE with SVM classifier. Considering the broader application of our findings, there is a limitation to the experimental design, which is the small number of subjects (only 31 healthy Koreans). In addition, the muscle activity data were recorded using surface electrodes in this study. Since it is difficult to place the electrodes consistently on the desired muscle, movement artifacts, electrical interference, and nearby muscle activity may have influenced muscle activation when acquiring data. Therefore, some spurious statistically significant findings may exist in these results. Future studies will be pursued and experiments will be conducted to obtain additional data by recruiting subjects.

The novel findings on gender-based differences in this study can provided useful gait information in clinical, medical, and rehabilitation field. Furthermore, our findings may be helpful for the development of healthcare device and system based on kinematics and electromyographic for males and females.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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