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Artificial neural networks in the selection of shoe lasts for people with mild diabetes

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ABSTRACT

This research addressed the selection of shoe lasts for footwear design to help relieve the pain associated with diabetic neuropathy and foot ulcers. A reverse engineering (RE) technique was used to convert point clouds corresponding to scanned shoe lasts and diabetic foot data into stereo lithograph (STL) meshes. A slicing algorithm was developed and was used to find relevant girth features of diabetic foot and the shoe lasts. An artificial neural network, termed self-organizing map (SOM), classified 60 sets of shoe lasts into similar groups. Foot shapes of three mild diabetic patients were entered into the SOM feature categories to match with suitable shoe lasts. By conducting expert questionnaire analysis of the characteristic girths featured data with analytic hierarchy process (AHP), the weights of the girths were obtained. Grey relational analysis (GRA) was then used to calculate the correlation between foot girth and the corresponding range of shoe lasts. The most suitable shoe last for each patient with a mild diabetic foot can be determined by calculating the relative fitness function for each patient. By correlating diabetic foot with suitable shoe lasts, this study demonstrated an effective strategy for designing shoes for patients with mild diabetes, which can then be manufactured to meet customized requirements.

1. Introduction

Foot ulceration is one of the many complications associated with diabetes. Design of bespoke footwear is a basic requirement for patients with diabetic foot problems. Diabetic patients often suffer from foot infections that can lead to foot ulcers, infections, gangrene, or amputation. At least 15% of diabetic patients will suffer from a foot ulcer at least once in their lifetime, which accounts for 50% of all cases of limb amputation without injury [1]. Diabetic foot ulcers result from nerve infection and/or ischemic blood vessels, with approximately 65% of foot ulcers triggered by nerve issues. Amputation cases caused by foot ulcers account for 85% of all cases, which is fifteen times higher than non-diabetic patients [2,3]. Foot ulcers affect quality of life and often result in a very difficult lifestyle. Therefore, it is important to investigate technologies that could potentially assist diabetic patients with finding suitable footwear that in addition to providing comfort may help to prevent foot ulcers.

1.1. Classification of the diabetic foot

The diabetic foot, first described in 1956, was defined as loss of feeling due to nerve affections [4]. In 1995, the World Health Organization (WHO) declared diabetes to be one of the top four major health issues in the world, in addition to hypertension, diabetic foot, ischemic heart, and cerebrovascular disease. For patients with diabetes, the design of customized shoe lasts represents a starting point for reducing the incidence of diabetic foot ulcers, amputations, and fatalities [5].

The Wagner grading system is the most widely used classification system for diabetic foot affections [6]. Wound classification can be used to identify the degree of a diabetic foot ulcer. The Wagner system includes an ulcer scale ranging from grade 0 to 5. Diabetic foot patients may receive different medical treatments depending on the severity of ulceration and associated complications. Our study was based on Wagner classification of diabetic neuropathic foot lesions. As shown in Table 1, Grade 0 patients are at risk of developing foot ulcers. The majority of people with dia-

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Table 1
The Wagner classification system for grading diabetic foot ulcers.

Grades	Characteristics
Grade 0	No foot ulcer, but at risk
Grade 1	Superficial ulcer of cutis or hypoderm
Grade 2	Deeper ulcer, possibly extended to bones, tendons, ligaments or articulus
Grade 3	Deep ulcer that causes affections of bone organization or abscess
Grade 4	Partial gangrene (toe or sole)
Grade 5	Extensive gangrene

betes (80%) are in Grade 0. Preventative measures can reduce the incidence rate of foot ulcers and can also reduce the rate of lower extremity amputation [7].

1.2. Shoe last design for the diabetic foot

Shoe lasts provide a comfortable internal shape to footwear and should correspond to the size and form of the foot. Shoe last design is of crucial importance to the functionality and fitness of footwear. Lasts are developed based on foot measurements taken of various age-specific and gender-specific populations. A foot size grading information system for shoe last design was established by a study that examined 2486 adult male feet [8]. A new surface joining method that uses blending and morphing techniques for the two halves of a given shoe last was proposed [9]. Knowledge-based design and CAD tool packages (*InfoHorma, LastDesigner*) were previously used in diabetic shoe last design [10]. In a previous study [11], 18 important foot features were extracted from a laser scan of a customer's foot. A CAD system used these data to deform the base of the customized shoe last to complement the customer's style preference, foot size, and shape.

Historically, diabetic shoes were usually designed to be practical rather than stylish to achieve the goal of protecting feet by providing stability when walking, reducing shock, distributing weight, and providing comfort. However, a majority of diabetic patients were unsatisfied with the appearance and functionality of conventional diabetic shoes, as they can be thick, heavy, and cumbersome. Patients also dislike shoes that are noticeably different from normal shoes, as this can bring further attention to their disease [12].

1.3. Footwear bio-modeling of a diabetic foot

Two different models are used to investigate the interaction between the foot and footwear [13,14]. First, a combined experimental and numerical approach is used for soft tissue, heel pad, and insoles. Second, a 3D bio-model is built and is sued to find the corresponding girths between shoe lasts and the foot.

In general, reduction of plantar pressure is a key issue in diabetic foot mechanics. A finite element model would provide an efficient computational framework for optimal reduction of plantar pressure. The relationship between the structural configuration and the mechanical functionality of the human plantar fat pad was previously investigated [15]. Phenomenological formulations describe the overall mechanical behavior of plantar fat pad tissue and are mandatory for investigating the overall structural response of the heel region in running shoes [16]. Insole design using finite element analysis to reduce plantar pressure relief was previously proposed [17,18]. Reducing plantar pressure is a biomechanical target [19].

Girth measurement is another way to investigate the relationship between shoe lasts and the diabetic foot. An increasing number of diabetic patients are wearing customized diabetic shoes instead of ready-made diabetic shoes [20,21]. A team of doctors, technicians, and researchers from the shoe manufacturing industry defined a broad set of measurements for diabetic shoe lasts [22]. In this study, 150 different foot shapes and 130 foot measurement parameters were evaluated. Seven characteristic girths were key features of shoe lasts, including last length, last width, ball girth, last girth, medium instep girth, high instep girth, and toe girth. Individual foot shapes were calculated as shown in Fig. 1. The seven characteristic girths listed above were used in our research to develop a customized diabetic shoe last.

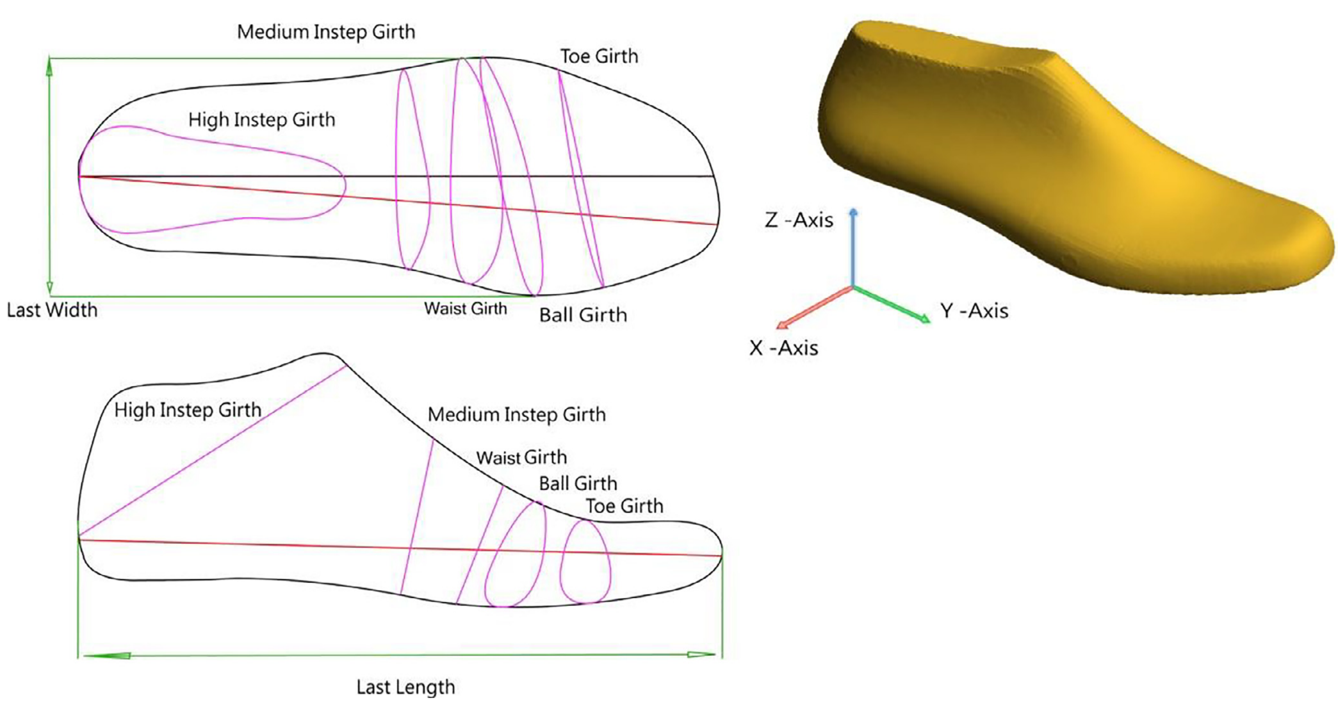

Fig. 1. Characteristic girths for diabetic shoe last design which includes: last length, last width, toe girth, ball girth, waist girth, medium instep girth, high instep girth.

The shoe last is the most important factor in shoe manufacturing. The best-fitted shoes are obtained when the shoe last is appropriate to a person's foot shape and size [23]. A customized 3D shoe last is essential or the production of diabetic bespoke shoes. An optimal shoe last design conforms to the shape of a patient's foot and also satisfies certain biomechanical conditions. Reducing plantar and dorsal pressure can prevent the development of a foot ulcer [24,25]. As opposed to mass production of shoes, mass customization of shoe development was proposed [26].

1.4. Aims of this research

The cost of making a new last is high, if a suitable shoe last can be selected quickly to fit a diabetic foot, then the cost will be down. The main purpose of this research is to design a process for selecting the most suitable shoe last for a Grade 0 diabetic foot. Through the feature girths of shoe lasts, footwear for patients with mild diabetes can be designed accurately and manufactured to achieve the purpose of reducing production costs and meet the customized requirements. A flowchart of the selection of the most suitable shoe last in this research is shown in Fig. 2.

The following key aims were addressed in this study:

(1) Scan 3D coordinates of the diabetic foot and shoe lasts.
A total of 60 shoe lasts were collected, which included 10 of each of the following sizes: 8, 8.5, 9, 9.5, 10 and 10.5. The right foot of three Grade 0 diabetic patients was scanned. Using a reverse engineering process, the 3D coordinates of the 60 shoe lasts and the three Grade 0 diabetic feet were transferred to point clouds.

(2) Capture characteristic girths of diabetic foot and shoe lasts.
The goal of aim 2 was to develop a system that automatically captures and analyzes foot characteristics as part of the shoe last design process. Seven characteristic girths of the shoe last and foot were included in this system: length, width, ball girth, waist girth, medium instep girth, high instep girth, and toe girth. A feature-based slicing algorithm in STL format (.stl) was developed for the automated capture and analysis of the seven characteristic girths. The STL data file is the de facto format for reverse engineering and 3D printing machines.

(3) Categorize shoe lasts using an artificial neural network (ANN) algorithm.
An automated clustering system was introduced by using a self-organizing map (SOM) algorithm in an ANN. A SOM reduces highly-dimensional input data into a map of two-dimensional figures by categorizing similar input items and plotting the similarities of the data. Based on the girths of the diabetic foot and shoe lasts, we used 60 shoe lasts as the training data to categorize them into groups. Comparing diabetic foot with each of the grouped shoe lasts, the most suitable grouped shoe lasts can be determined.

(4) Establish the diabetic foot fitness function.
The analytic hierarchical process (AHP) was used to deal with the weights of the characteristic girths. Grey relational analysis (GRA) emphasized the relationship between the diabetic foot and the grouped shoe lasts in the corresponding girths. Finally, the fitness function based on weights of girths and grey relational grade was examined and the optimal shoe last for the mild diabetic patient can be determined.

2. Methods

Customized diabetic shoes can be designed from the feature-based shoe lasts selection process. In this study, selected shoe lasts were categorized via the ANN learning algorithm to find a suitable group of shoe lasts for the diabetic foot. The AHP and GRA methods were used to determine the fitness function of the diabetic foot. A Matlab program was developed based on the slicing algorithm for characteristic girths and a SOM in a neural network. The program was used to categorize shoe lasts as part of identifying optimal shoe lasts for the diabetic foot.

2.1. Measurements of reverse engineering

A prediction method for modeling foot shapes by using limited parameters in reverse engineering to scale a standard foot was previously proposed [27,28]. This prediction method provided a low-cost 3D foot-scanning method for use in the development of footwear in the mass-customization industry. Nonintrusive laser scanners were utilized in this study to capture reverse engineering measurements and to acquire data for point clouds that were used to derive 3D space data of shoe lasts and diabetic foot profiles (Fig. 3). Point clouds data corresponding to shoe lasts and foot profiles were merged with noise elimination and the 3D reverse engineering software, *Geomagic*, was used to obtain point cluster reduction (Fig. 4). Subsequently, the data was transformed into triangular meshes and saved as STL files in ASCII format for follow-up reading and handling [29–31].

2.2. Capture of foot shape and shoe last features

Prior to foot characteristic and shoe last girths analysis, the objects were placed in the same world coordinate system so that they can be rotated and moved to the correct position to allow for determination of corresponding characteristic girths. In this study, the x-axis represented the direction in width of the shoe last and foot, the y-axis represented the direction in length, and the z-axis represented the direction in height (Fig. 5) [32,33].

An automated slicing procedure was built and was used to capture the girths of shoe lasts and of the diabetic foot. The slicing algorithm used a plane to intersect with the STL file to obtain the important girth characteristics of foot lasts and diabetic feet in the same location. These foot and shoe last girth characteristics included length, width, ball girth, waist (last) girth, medium instep girth, high instep girth, and toe girth. The STL files corresponding to a shoe last profile and foot shape were utilized to determine each dimension, with calculations and capture of characteristic measurements [34–36]. A platform by using Matlab software to establish shoe last and diabetic foot girths in a windows graphic user interface (GUI) was built. The features of the seven girth characteristics for shoe lasts and diabetic foot are shown in Fig. 6.

2.3. Self-organizing map for the diabetic foot

Self-organizing map (SOM) is a type of unsupervised learning system in the artificial neural networks (ANN). The training of the SOM is entirely data driven, with no target results for the provided input data vectors. SOM provides topology-preserving mapping from a high-dimensional space onto a two-dimensional plane to serve as a cluster analyzing tool for reducing the dimensions [37].

An ANN for predicting dorsal pressure on the foot surface while walking was previously reported [38]. Dorsal pressure is a good way of measuring comfort and functionality of footwear. A competitive learning system in the SOM for categorizing 50 sneakers for top NBA point guards was previously proposed [39]. A back-propagation neural network (BPN) was used to verify the mapping of sneakers for these point guards. The results were validated by comparison with target nodes, based on the SOM feature map. Running shoes were used as the primary research object along

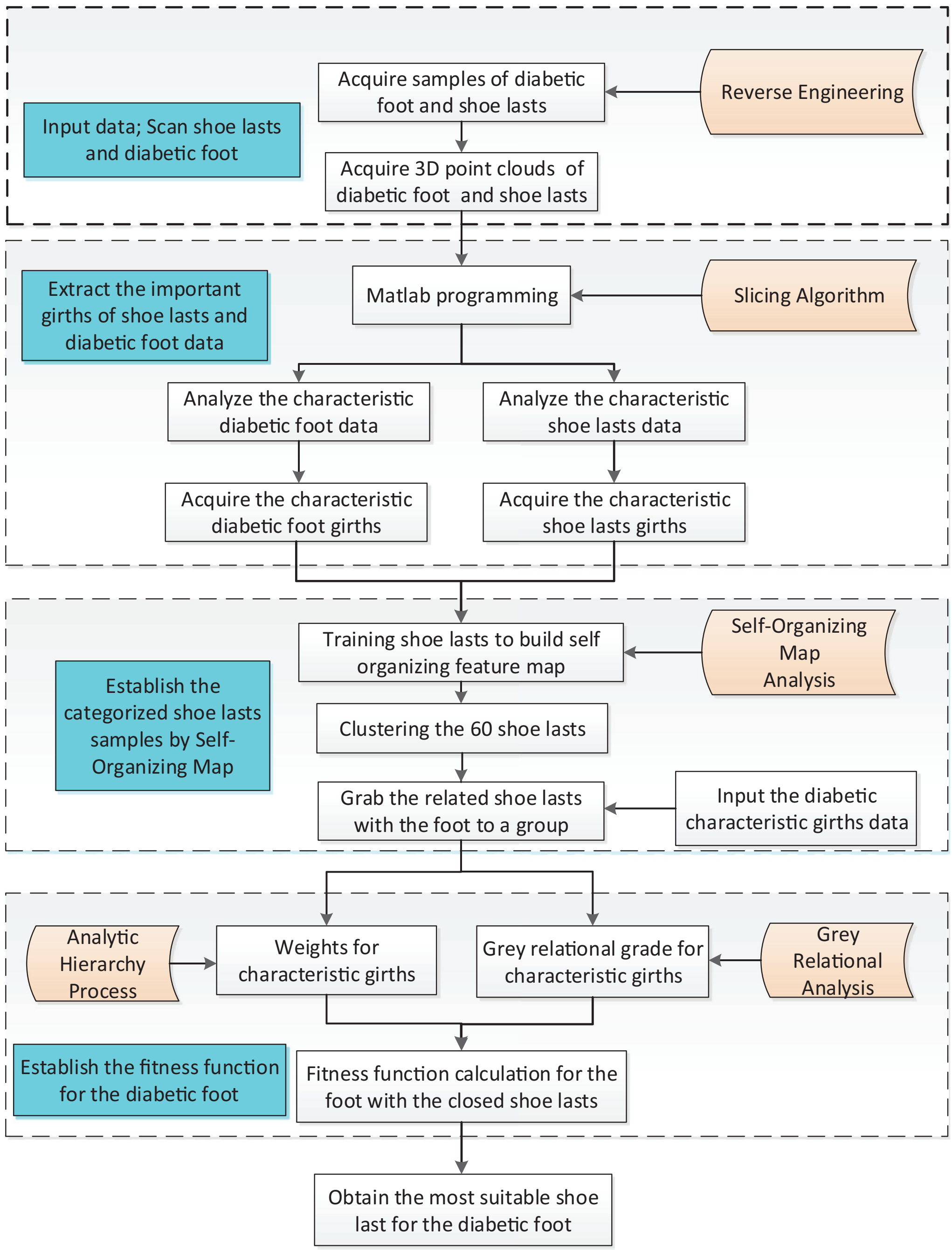

Fig. 2. Flowchart to select the most suitable shoe last for a mild diabetic foot.

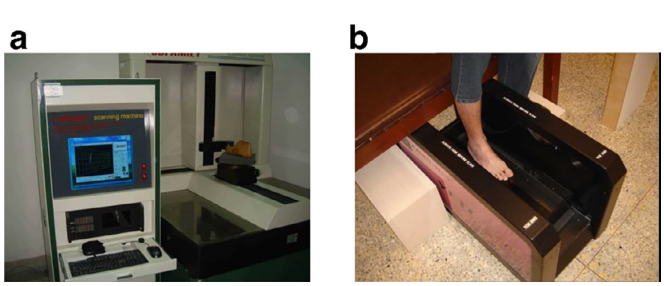

Fig. 3. 3D scanning measuring machine used in this research. (a) Reverse scanning machine for shoe last measurement, (b) diabetic foot profile scanning process.

with Kansei questionnaires, principal component analysis (PCA), partial least squares (PLS), and neural network to develop a design support system for the exterior form of running shoes [40].

Using the SOM algorithm to group similar shoe lasts and to find the most suitable shoe last for the diabetic foot was the main topic of this research. A SOM neural network can categorize all 60 input shoe lasts into related groups. Diabetic foot girths were then compared with shoe lasts to find suitable clustered shoe lasts. The structure of the SOM neural network used to categorize diabetic feet to the corresponding shoe last group is shown in Fig. 7.

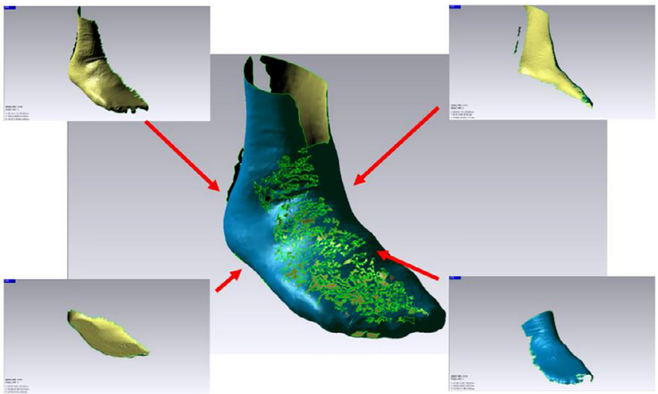

Fig. 4. Merging a foot shape from scanning different views of point clouds.

2.4. Analytical hierarchy process

Analytical hierarchy process (AHP) is considered to be a good decision-making methodology. AHP deals with interdependencies among the criteria in the weights of girths [41]. AHP is a preferred and reliable tool since it ranks the evaluation criteria according to their relative importance. AHP assesses decision points for every factor and uses a mathematical eigenvector method to find the percentage distribution of decision points in terms of the weights that affect the decision [42]. We used AHP in this research to determine the weights of the five most important girths, including ball girth, waist girth, medium instep girth, high instep girth, and toe girth.

2.5. Grey relational analysis

Grey relational analysis is a relational correlation methodology for small sample numbers and uncertain situations. GRA discusses and understands the situation of the system by prediction and decision making aimed at system uncertainty and information incompleteness [43,44]. In this research, GRA determines uncertainties in factors concerning a given diabetic foot and the corresponding shoe lasts. GRA aims to find the correlation between diabetic foot girths and the related shoe lasts.

3. Experiments and results

3.1. Extraction of girth dimensions

Shoe last models and foot models were inputted in triangular meshes in STL ASCII format. The developed program used the slicing algorithm to calculate the length, width, ball girth, waist girth, medium instep girth, high instep girth, and toe girth of all shoe lasts and diabetic foot. Numerical data of all characteristic girths were stored in an Excel file, which was used in the subsequent SOM neural classification process. This served as experimental validation data, with each foot undergoing coordinate transformation and matching with a shoe last profile from the STL file. The girth data for the three diabetic foot are shown in Table 2.

3.2. SOM feature-based construction

SOM can categorize 60 shoe lasts and three diabetic feet into a specific matrix. The structure of a self-organizing feature map

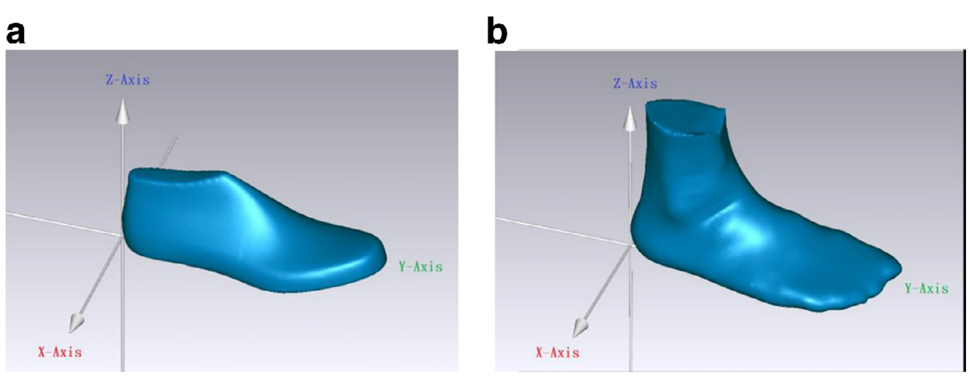

Fig. 5. World coordinate system for shoe last feature and foot shape capture. (a) The shoe last coordinate system, (b) the foot coordinate system.

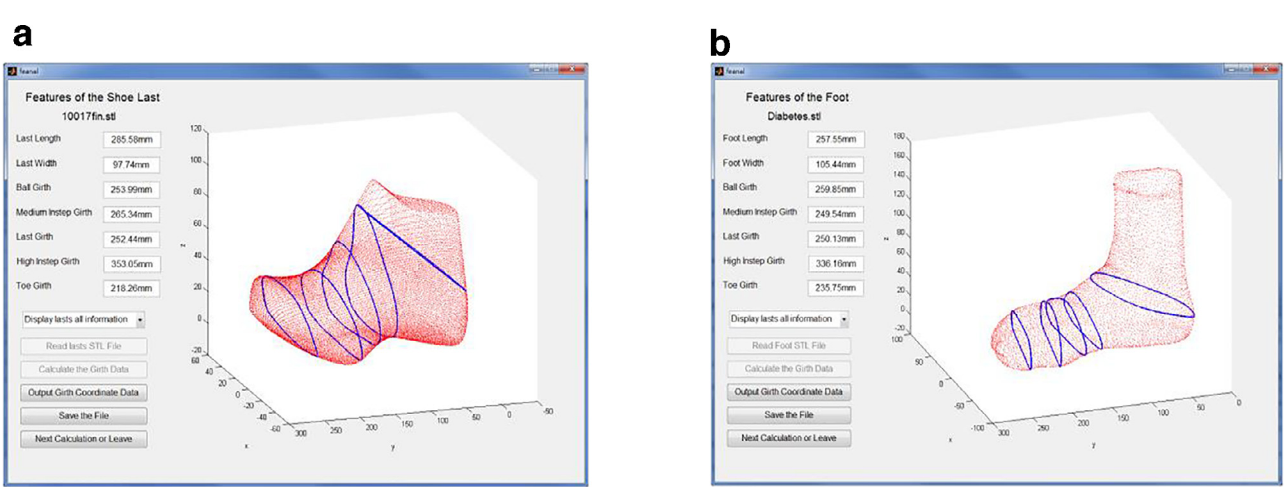

Fig. 6. Features of seven important girths profile for shoe lasts and diabetic foot. (a) Feature girths of shoe last shape, (b) feature girths of diabetic foot shape.

Table 2
Seven important girth data from measurements of three mild diabetic foot.

No.	Length (mm)	Width (mm)	Ball girth (mm)	Waist girth (mm)	Medium instep girth (mm)	High instep girth (mm)	Toe girth (mm)
1	257.56	105.45	259.85	250.13	249.54	336.16	235.75
2	259.44	99.53	242.44	244.89	235.96	343.33	216.48
3	260.66	102.55	251.82	254.03	243.67	345.44	232.43

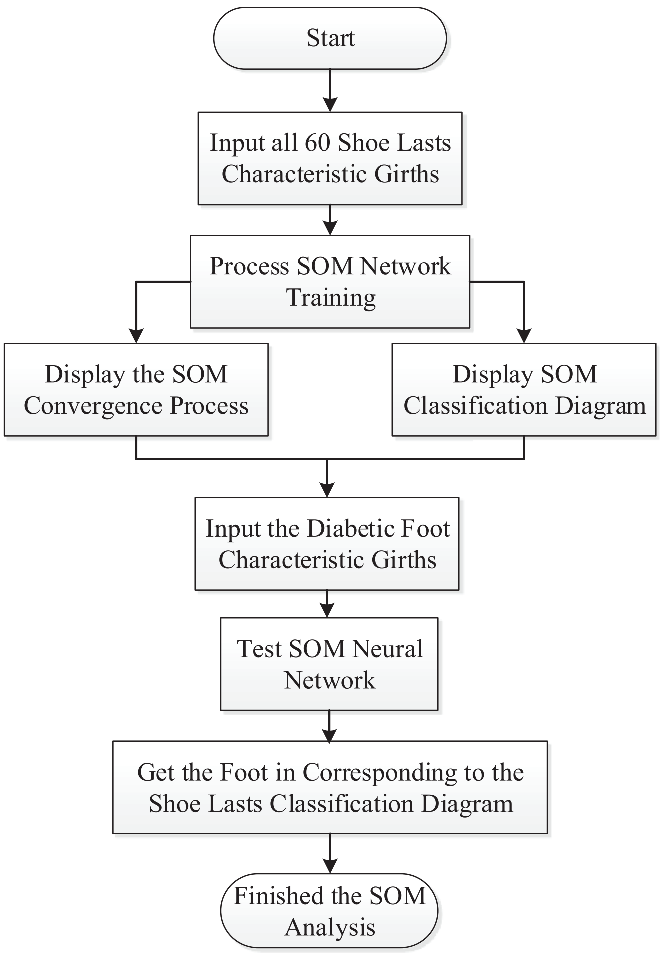

Fig. 7. Systematic flowchart using SOM algorithm to categorize shoe lasts and the corresponding diabetic foot.

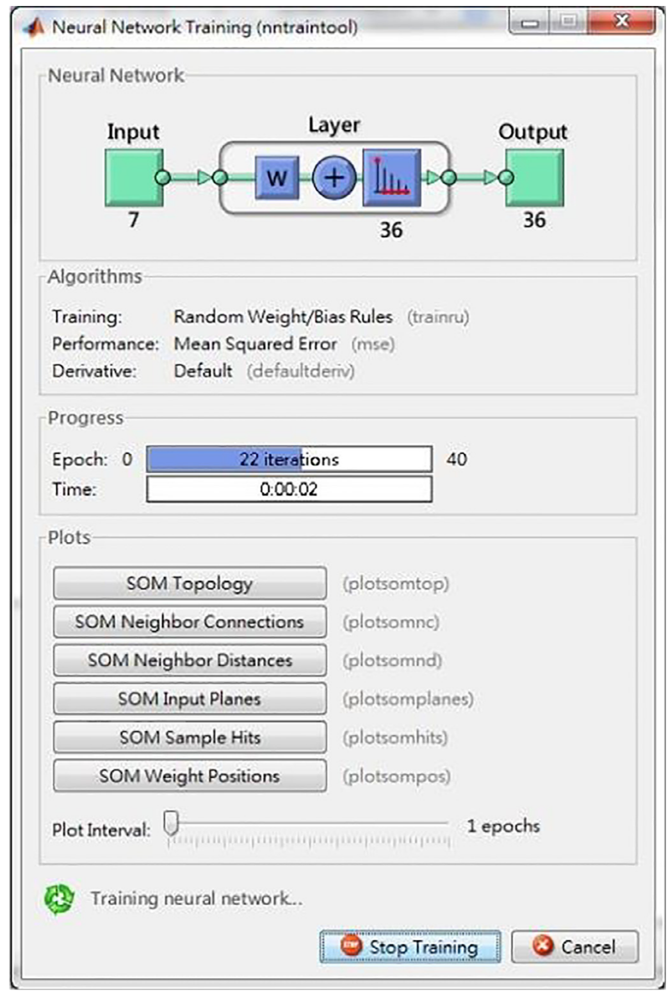

Fig. 8. SOM neural network training progress for 60 shoe lasts in Matlab.

Table 3
Setting SOM networking parameters and their attributes for shoe lasts categorization.

Parameters	Attributes
Input layer nodes (girths)	7
Sampling data (shoe lasts)	60
Output layer dimension	2
Output layer nodes	6 × 6 (36)
Initial learning rate	1
Initial neighbouring radius	1
Training times	100

includes an input layer, an output layer, and the weights transferred between the input/output layers. SOM networking parameters and their attributes are listed in Table 3.

For the input layer, the seven girth characteristics served as the input nodes or characteristic vectors. All 60 shoe lasts were used as individual dimensions in the training samples. The output layer of the SOM can map training samples into a two-dimensional matrix based on characteristic similarities. Typically, the output nodes of SOM are set at 60–70% of the input samples [34,37]. With fewer nodes, SOM cannot distinguish differences between samples but with too many nodes, the samples may separate from each other. In our work, for 60 training samples with 60% of the sampling data, we set the number of output nodes for shoe lasts to 36 (6 × 6 in two-dimensional space), as shown in Fig. 8. The result of SOM neural networks for 60 shoe lasts training and matching with 3 diabetic foot can be shown in Fig. 9.

3.3. Weights of the characteristic girths

By gathering comments and evaluations from three diabetic shoe experts (diabetic patient, doctor, and shoe maker), a pair-wise comparison matrix of factors was created through AHP according to a nominal scale. The priority vector and maximum eigenvalue were then determined and the results were evaluated to determine consistency. The eigen method was used to solve AHP. The eigenvectors w obtained from the pair-wise comparison matrix included

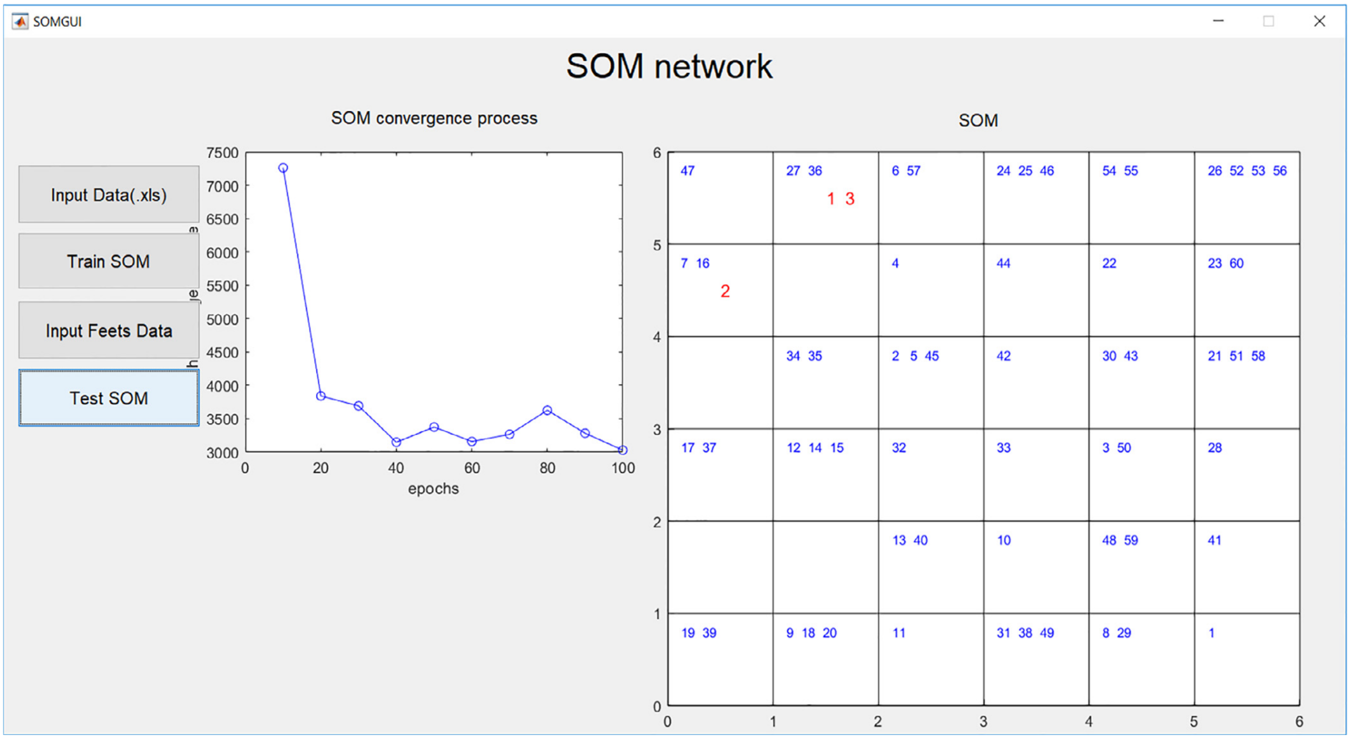

Fig. 9. SOM neural networks for clustering 60 shoe lasts and three diabetic foot.

Table 4
Using AHP algorithm to transfer results from questionnaire to girths weight.

Questionnaires no.	Pairwise comparison matrix	$\lambda_{\max}$	*CI*	*w*
1	$\begin{pmatrix} 1 & 7 & 9 & 3 & 1 \\ 1/7 & 1 & 1/3 & 1/3 & 1/9 \\ 1/9 & 3 & 1 & 1/5 & 1/9 \\ 1/3 & 3 & 5 & 1 & 1/5 \\ 1 & 9 & 9 & 5 & 1 \end{pmatrix}$	5.3202	0.0800	$\begin{pmatrix} 0.358 \\ 0.035 \\ 0.048 \\ 0.138 \\ 0.422 \end{pmatrix}$
2	$\begin{pmatrix} 1 & 9 & 9 & 5 & 1 \\ 1/9 & 1 & 1/3 & 1/3 & 1/9 \\ 1/9 & 3 & 1 & 1/3 & 1/7 \\ 1/5 & 3 & 3 & 1 & 1/5 \\ 1 & 9 & 7 & 5 & 1 \end{pmatrix}$	5.1878	0.0470	$\begin{pmatrix} 0.417 \\ 0.033 \\ 0.055 \\ 0.106 \\ 0.390 \end{pmatrix}$
3	$\begin{pmatrix} 1 & 7 & 9 & 5 & 1 \\ 1/7 & 1 & 1/3 & 1/3 & 1/9 \\ 1/9 & 3 & 1 & 1/3 & 1/7 \\ 1/5 & 3 & 3 & 1 & 1/5 \\ 1 & 9 & 7 & 5 & 1 \end{pmatrix}$	5.2297	0.0574	$\begin{pmatrix} 0.409 \\ 0.035 \\ 0.055 \\ 0.107 \\ 0.393 \end{pmatrix}$

the weights related to all factors. After determining the eigenvector, the results must be examined for consistency. Satty [42] proposed the Consistency Index (*CI*):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (1)$$

where $\lambda_{\max}$ is the largest (or principal) eigenvalue of the comparison matrix and n is the number of factors (or the order) of the comparison matrix. In general, if $CI \le 0.1$, the matrix is consistent and the eigenvectors w obtained from the matrix can represent the weights related to all factors, where $w = [w_B \quad w_W \quad w_M \quad w_H \quad w_T]^T$, w_B: weight for ball girth; w_W: weight for waist girth; w_M: weight for medium instep girth; w_H: weight for high instep girth; w_T: weight for toe girth, as shown in Table 4.

Following generation of the AHP results, we used the geometric mean value to find the total weight of each girth. The total girth weights were $w = [0.394 \quad 0.034 \quad 0.053 \quad 0.116 \quad 0.401]^T$ which indicates that toe girth and ball girth are the most important girths of a diabetic foot.

3.4. Grey relational grade

The mapping process in SOM networks can only provide a grouped separation among the 60 shoe lasts and 3 diabetic foot. Grey relational analysis was used to conduct a relational correlation analysis among these uncertainties. For example, we checked an uncertain related discrete sequence (two shoe lasts, No. 27 and No. 36) and its target (a diabetic foot, No. 1) from the SOM map (Fig. 9). The girths for foot No. 1 and the related shoe lasts are shown in Table 5. The sequence complied with the comparability conditions of normalization to generate a new grey relational sequence. The grey relational grade (GRG) was obtained from the grey relational coefficient following its calculation. As shown in Table 6, G_B = Ball Girth Correlation; G_W = Waist Girth Correlation; G_M = Medium Instep Girth Correlation; G_H = High Instep Girth Correlation; G_T = Toe Girth Correlation [43,45].

Table 5
Girths data for patient No. 1 and the most related shoe lasts (No. 27 and No. 36).

Patient No. 1/Lasts No. 27 and 36	Ball girth (mm)	Waist girth (mm)	Medium instep girth (mm)	High instep girth (mm)	Toe girth (mm)
Patient No. 1	259.85	250.13	249.54	336.16	235.75
Last No. 27	253.09	254.56	247.93	341.70	231.51
Last No. 36	248.93	259.04	247.10	342.96	226.61

Table 6
Grey relational grades for patient No. 1 and the most related shoe lasts (No. 27 and No. 36).

Shoe lasts v.s. Patient No. 1	G_B, Ball girth	G_W, Waist girth	G_M, Medium instep girth	G_H, High instep girth	G_T, Toe girth
Last No. 27	0.7986	0.8422	0.9241	0.8287	0.8634
Last No. 36	0.7105	0.7383	0.8984	0.7976	0.7457

3.5. Fitness function

By using the weights for each girth from AHP process and grey relational grade in all girths for a certain diabetic foot, the fitness function can be expressed as the comfort value for a diabetic foot compared with a related shoe last [34].

The fitness function F is defined as:

$$F = w_B G_B + w_W G_W + w_M G_M + w_H G_H + w_T G_T \tag{2}$$

where F is the fitness function for the total evaluation of the diabetic foot and the shoe last girths. The best fit shoe last for each examinee's foot can be determined from the fitness function calculation. For the case of the No. 1 diabetic foot, the fitness function among the related shoe lasts group can be calculated as follows.

$$F_{27} = 0.394 \times 0.7986 + 0.034 \times 0.8422 + 0.053 \times 0.9241 + 0.116 \times 0.8287 + 0.401 \times 0.8634 = 0.8346$$

$$F_{36} = 0.394 \times 0.7105 + 0.034 \times 0.7383 + 0.053 \times 0.8984 + 0.116 \times 0.7976 + 0.401 \times 0.7457 = 0.7442$$

From the results of the group related shoe lasts for No. 1 diabetic foot, the values followed this order, $F_{27} > F_{36}$, which meant that among the 60 shoe lasts, No. 27 would be the most suitable for the No. 1 diabetic foot.

4. Discussion and conclusions

This study developed a method for selecting an optimal shoe last for a mild diabetic foot. A self-organizing feature map in artificial neural networks was used to categorize the 60 selected shoe lasts into similar groups based on seven girth parameters. A fitness function was used to determine the most suitable shoe last for each diabetic foot.

Customized diabetic shoes are limited by higher manufacturing costs and higher consumer prices. This study proposed a simple, customized shoe lasts selection process for cases of mild diabetes. Reverse engineering measurements generated an accurate data profile for shoe lasts and diabetic feet. 3D point clouds established characteristic girths using a slicing algorithm with triangular meshes. Clustering calculation performed by the SOM neural network on the shoe lasts data and the system generated results that can rapidly determine the most suitable shoe last for any mild diabetic patient.

Different conditions, such as weather, time of day, and air pressure can cause foot girths to expand or shrink. According to shoe last designers and shoemakers, the ball, waist, instep, and heel girths of shoe lasts are 5–10 mm smaller than the corresponding structures in the human foot [8,12]. There is no precise scientific algorithm for calculating girth tolerance between shoe lasts and the foot. A sense of threshold fuzzy analysis algorithm was introduced for evaluating the difference between the shoe lasts and the foot [34]. However, using fuzzy algorithm to conduct pairwise comparisons of shoe lasts with foot is very time-consuming. In this study, we proposed an artificial intelligence method for finding the best shoe last dataset for a mild diabetic foot. A neural network algorithm was developed for creating a self-organizing feature map. The SOM categorizes the appropriate shoe last group for each diabetic patient, which reduces the uncertainty associated with selecting a suitable shoe lasts group.

A platform was built for selecting shoe lasts for mild diabetic feet. Matlab software was used to code a program for selecting the appropriate shoe last for a diabetic foot based on the 3D point cloud bio-models of shoe lasts and diabetic feet. A slicing algorithm was developed and applied in a system for reading STL model data of diabetic feet and shoe lasts. This system can automatically measure and capture related girth characteristics of shoe lasts and diabetic feet, which reduces errors as compared to the manual measurements. This study demonstrated a very useful solution to the challenges faced by diabetics when selecting shoe lasts.

Both a shoe's fitness and aesthetic design are paramount in shoe design. The present research may transform traditional shoe design processes. The style of diabetic footwear is another issue worth studying and may be address, for example, by Kansei perception and aesthetic design. In this research, we established a good evaluation in fitness function for the diabetic foot with related shoe lasts by using AHP and GRA algorithms. The most suitable shoe last for a mild diabetic foot is identified during the evaluation.

In the future, increasing the number of shoe last samples will increase the size of the shoe database and adding more girth considerations will make the process of finding the most suitable lasts more precisely and fast, yielding fully customized footwear for patients with mild diabetes.

Conflicts of interest

There are no conflicts of interest to declare.

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Ethical approval

Not required.

Appendix. SOM for shoe lasts training and diabetic foot matching in Matlab

As shown in Fig. 9, a user-friendly Graphic User Interface (GUI) program was developed in Matlab for diabetic foot analysis. This diabetic platform is separated into four portions, including inputting all shoe lasts in Excel format, training SOM for all shoe lasts, inputting diabetic foot data, and categorizing SOM for the diabetic feet corresponding to the shoe lasts group.

The girth data in Excel file for the 60 shoe lasts was inputted into the system by pressing the button "**Input Data(.xls)**" and the training process initiated after pressing the "**Train SOM**" button. After 100 iterations, the neural network converged and the 60 shoe lasts were clustered together based on similarity. The topological output for the 60 shoe lasts can be mapped into a 6×6 table. Because each input data contains various initial weights, the corresponding and adjusted winning nodes were not the same. As a result, clustering groups are not always the same. However, the related samples (shoe lasts) will appear in the same group.

After training all 60 shoe lasts, girth data of the three mild diabetic feet were input by pressing "**Input Feet Data**". Finally, by pressing "**Test SOM**", the system assigned the foot style into a certain group of shoe lasts, which was mostly based on the SOM algorithm. The results indicated that diabetic foot No. 1 and No. 3 matched shoe lasts No. 27 and No. 36. Diabetic foot No. 2 matched with shoe lasts No. 7 and No. 16.

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