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(54) **Title**: SYSTEM AND METHOD FOR FIT PREDICTION AND RECOMMENDATION OF FOOTWEAR AND CLOTHING

(57) **Abstract**: A method includes identifying an ordering client and a desired wearable item, and identifying a plurality of wearable items that are associated with the ordering customer. The ordering customer has tried on at least a portion of the plurality of wearable items. The method also includes identifying at least one specified body shape similarity degree for each of the plurality of wearable items associated with the desired wearable item, and obtaining an estimated fit score for the desired wearable item with respect to the ordering customer.

SYSTEM AND METHOD FOR FIT PREDICTION AND RECOMMENDATION OF FOOTWEAR AND CLOTHING

[0001] This application claims priority to U.S. Provisional Application 61/052,294, titled “System and method for fit and aesthetic prediction and recommendation of footwear and clothing”, and filed 12-MAY-2008, the entire disclosure of which is incorporated by reference.

TECHNICAL FIELD

[0002] The present invention relates to fit prediction of footwear or clothing to a customer and recommending footwear or clothing to a customer, using only the purchase / return or fitting records, without physically trying on the item and without having to take measurements of the foot or body, or having to use measurements of the footwear or clothing item.

BACKGROUND

[0003] With the rapid advancements of online sales and the fast-expending choices in brands, styles and functions, fit prediction of footwear and clothing is an important issue.

[0004] For online retail, and other categories of remote retailer, such as catalog mail order, customers will have no chance to actually try on footwear and clothing of interest before the order is delivered. If the fit turns out to be less than satisfactory upon receiving the order, customer will have to return the products, which incur inconvenience and costs for both customers and the online retailer.

[0005] For brick-n-mortar retailers, the vast choices in brands, geometry and measurements mean that it is time-consuming and hence costly for customers to actually try-on all interested footwear or clothing.

[0006] In response to the increasing demand for customized products, today’s manufacturing is transitioning from traditional standardized manufacturing to post-industry-age manufacturing modes, such as “customer-centric”, “mass-customization”, and “service-oriented” manufacturing. The clothing, footwear, and other wearable items such as hats industries may be an ideal starting point to implement customization because these products naturally require a higher level of

customization and can benefit more from customization by virtue of improving customer satisfaction. One key feature of this transition is the proliferation of product feature, and finer granularity of sizes for customers to choose from. Take the footwear industry as an example, this means to take more foot measurements into consideration and apply finer granularity in terms of sizing for each measurement. The result will be a more choices in size to gradually improve overall fit satisfaction for all customers. With more choices in sizes and more foot measurements being considered for fit, the process of choosing the right footwear for a customer becomes increasingly complex. Because the search process no longer trace a single dimension, such as length, with relatively big step, half an inch for US size scheme as an example, the search now is done in a multi-dimensional space with smaller steps.

[0007] For both online and brick-n-mortar retailers, it is desirable to have an effective method to predict fit quality of footwear and clothing and recommend good-fitting items to any particular customer.

[0008] With regard to fit prediction, prior arts include the traditional sizing scheme, and more recently the 3D scanning and measuring technologies.

[0009] The traditional sizing scheme divide the product size into predefined incremental changes, such as the US footwear men's sizes of 8, 8.5, 9, 9.5, 10, 10.5, 11, 11.5, 12, 12.5, and 13. The problems with the traditional sizing scheme is evident, and many consumer can tell from their own personal experiences that they fit different sizes of footwear and clothing from different brands and across different product lines, functions and styles. The root of this problem may lie in that different countries may adopt different sizing schemes and different brand manufacturers use different design standards. Designing footwear and clothing is based on experimental data and experiences accumulated over decades. And different brands and design houses adopt different standards. For example, for square-toed man's dress shoes, the length of the toe-box is relaxed by a certain amount beyond the tip of the toe for a certain size of shoes. According to many academic and industry sources, different brands use different rules regarding this type of "relaxation", hence for a particular customer some shoes will run "small", and some run "true", while others run "large" even if the nominal sizes are all the same.

[0010] 3D scanning and measuring of the human foot and whole body for fit prediction has been described in many prior arts. This approach can be summed up as measuring linear and circumferential, or girth, dimensions on the acquired 3D model of the foot and body, and compare these measurements with corresponding dimensions of the particular footwear or clothing item to predict footwear or clothing item fit quality. For footwear, shoe last is usually used to represent the internal shape of the particular shoe. Shoe last 3D information is usually available as shoe lasts are increasingly designed using 3D CAD tools. While 3D scanning is a step forward compared with traditional sizing scheme, it has not seen wide-spread application because the direct comparison of foot or body shape measurements with footwear or clothing is inherently expensive to implement.

[0011] All 3D scanning solutions capture the foot or body in a static state, while standing straight on a flat surface. The human body is a complex and deformable anatomy that changes shape during walking, running, standing, sitting etc. By comparison of 3D shape and measurements of static body and foot with those of the clothing and footwear to predict fit quality missed the vast majority of instances when the body or foot is not in the static state. Further, for women's high-heel shoes, the acquired 3D foot models have to be deformed before they can be compared to shoe lasts. So far, there has not been a reliable deform method to produce consistent results.

[0012] Fit quality may be ultimately subjective and depends on individual preferences. Some may prefer a shoe loose at toe while others may prefer the shoe to be tight at heel, etc. As such, any fit prediction method relying solely on hard, objective, and direct comparison of geometry and measurements between footwear/clothing and foot/body may have certain limitations.

[0013] The present invention aims to solve one or more of the problems or disadvantages associated with the prior art

SUMMARY

[0014] For purposes of illustration and simplicity, the embodiments presented in this specification focus primarily on footwear. However, it is understood that other embodiments of the present invention can be applied to any style of footwear,

clothing, gloves, masks, hats, helmets, eye glasses and other wearable items a person may wear to the body, when fit is an important factor in satisfaction but difficult to ascertain without actual try on. In such cases, the present invention can help predict fit quality and recommend good-fitting items without actual try on. It will be further understood that the described examples and arrangements of the present invention are merely illustrative of applications of the principles of this invention and many other embodiments and modifications maybe made without departing from the spirit and scope of the invention.

[0015] Wearable items refer to products a person would wear to the body, such as clothing, footwear, hats, gloves, eyeglasses, and so on. A category of wearable item can be footwear, jacket, pants, sweater, shirt, underwear, underpants, hat, glove, or eyeglasses, etc.

[0016] The present invention exploit past purchase/return or fitting records of a group of customers to a library of wearable items to make fit prediction for a customer to a wearable item not yet tried.

[0017] Wearable items are designed for Specified Body Shapes. In the case of shoes, each model of shoe in a particular band, style, and size is designed to fit a particular foot shape and set of measurements. These measurements are used to design a shoe last which defines the internal shape of the shoe. In the case of clothing, fabric is cut to fit certain size body perfectly. For shoes, Specified Foot Shape is the foot shape and set of foot measurements on which the shoe is made to fit perfectly. For clothing, Specified Body Shape is the body shape and set of body measurements on which the clothing is made to fit perfectly. How these specified sizes match actual customer body sizes will not only determine fit comfort of customers, but also affect health. The concepts of “Specified Body Shape” and “Specified Foot Shape” are introduced because an item of footwear, clothing, or other categories of wearable items are not rigid and do not have an innate shape of their own. The “Specified Body Shape” of the wearable item is the corresponding shape of the body part the wearable item will fit perfectly. The “Specified Body Shape” represents the fitting characteristics of a wearable item.

[0018] The present invention is based on these assumptions: that the body shape or foot shape of an adult customer remains relatively stable over time; that

similarities in body shape or foot shape exist between the customers; and that similarities in Specified Foot Shape of footwear or Specified Body Shape of clothing exist between two different styles of shoes or two different styles of clothing, respectively. Based on these assumptions, customers' purchase/ return or fitting records can be used to predict fitting to footwear or clothing not yet tried.

[0019] Customers, who share similarities in purchase/return or fitting records in clothing or shoes, will necessarily have similarities in their body shape or foot shape respectively. Based on this principle, we can derive similarities in body shape or foot shape among different customers. This method maybe regarded as "using clothing to measure body" or "using shoes to measure foot", and to determine similarities among customers. Proper clothing or shoes can be chosen for a customer without actually try on. In essence, this method let other customers who fit the same shoes or clothing as you in the past try on new shoes or new clothing for you.

[0020] Similarly, purchase/return or fitting records can be used to determine similarities in wearable items. Clothing or footwear items fit to the same customer will have similarities in their Specified Body Shape or Specified Foot Shape and are interchangeable to some extent; For example, if a customer fit well to two different pairs of shoes, then there must be similarity between the specified foot shapes of these two pairs. If another customer also find one of the two pairs a good fit, it is very likely that this other customer will also find the other pair to be a good fit. The two pairs of shoes, while can be of different brand, style and nominal size, are interchangeable in terms of fit characteristics. Based on this principle, fit quality of wearable items can be predicted. In essence, this method may be regarded as "using body to measure clothing", "using foot to measure shoes". There exist no better measuring device than the wearer's body and foot which can sensitively and reliably measure the static and dynamic fit quality over short-term and long-term.

[0021] The present invention develops the aforementioned concepts and ideas into an integral system.

BRIEF DESCRIPTION OF THE DRAWINGS

[0022] Referring now to the drawings, illustrative embodiments are shown in detail. Although the drawings represent some embodiments, the drawings are not necessarily to scale and certain features may be exaggerated, removed, or partially

sectioned to better illustrate and explain the present invention. Further, the embodiments set forth herein are exemplary and are not intended to be exhaustive or otherwise limit or restrict the claims to the precise forms and configurations shown in the drawings and disclosed in the following detailed description

[0023] The accompanying drawings, which are incorporated in and constitute a part of this specification, illustrate a system consistent with the invention and, together with the description, serve to explain the principles of the inventions.

[0024] Figure 1A shows a data structure of purchase and fitting rating database and example data entries, according to an embodiment.

[0025] Figure 1B shows the same data entries as Figure 1A, but arranged in a different manner.

[0026] Figure 2 shows a forward search, which looks for items which a customer has purchased; and a reverse search, which looks for customers who have purchased an item.

[0027] Figure 3 shows that a forward search beginning with a customer and followed by a reverse search to find other customers who purchased same ID items as the customer.

[0028] Figure 4 shows sub-sets discovered through an iterative forward and reverse search until convergence.

[0029] Figure 5 shows some of the customers resulting from an iterative forward and reverse search.

[0030] Figure 6 shows a customer set divided into sub-sets.

[0031] Figure 7 shows the item set divided into sub-sets.

[0032] Figure 8A shows Foot Shapes Similarity Degree (%) between two customers, under different α values and the number of pairs of same ID footwear purchased, n.

[0033] Figure 8B shows “Foot Shape Similarity Degree (%) between two customers” vs. “number of the same ID items purchased by two customers” is a kind of saturated curve.

[0034] Figure 9 shows indirect calculation of Foot Shape Similarity Degree based on its transitive attribute.

[0035] Figure 10 shows an alternative method to calculate Specified Foot Shape Similarity Degree between two footwear items.

[0036] Figure 11 shows a Foot Shape Similarity Network with directly and indirectly calculated Foot Shape Similarity Degrees.

[0037] Figure 12 shows a Foot Shape Similarity Network of customers and its sub-networks.

[0038] Figure 13 shows a Specified Foot Shape Similarity Network of footwear items and its sub-networks.

[0039] Figure 14 shows a clustering method to further divide customers in a Foot Shape Similarity Sub-Network into clusters based on a similarity degree threshold.

[0040] Figure 15A summarizes and clarifies the terms “Customer Set”, “Sub-set”, “Customer Network”, “Sub-networks” and “Customer clusters”.

[0041] Figure 15B summarizes and clarifies the terms “Item set”, “Item Sub-set”, “Item Network”, “Sub-networks” and “Item clusters”.

[0042] Figure 16 shows an example of customers’ Fitting Rating and Fit Score form for footwear items.

[0043] Figure 17 shows a calculation of Minor Difference between foot shapes of customers and the correction in their Foot Shape Similarity Degrees based on customers’ Fitting Ratings.

[0044] Figure 18 shows a calculation of Minor Difference between specified foot shape footwear items and the correction in their Specified Body Shape Similarity Degrees based on customers’ fitting ratings.

[0045] Figure 19 shows an example of “virtual try on”.

[0046] Figure 20 shows one method of fit prediction of a footwear item to a customer, without customer Fitting Ratings.

[0047] Figure 21 shows another method of fit prediction of a footwear item to a customer, without customer Fitting Ratings.

[0048] Figure 22 shows one method of fit prediction of a footwear item to a customer, with customer Fitting Ratings.

[0049] Figure 23 shows another method of fit prediction of a footwear item to a customer, with customer Fitting Ratings.

[0050] Figure 24 is an example showing the relation between predicted customers' fitting rating and returning ratio of the item purchased.

[0051] Figure 25 provides an overall summary of some of the concepts and procedures disclosed, according to an embodiment.

DETAILED DESCRIPTION OF THE DRAWINGS

[0052] Reference will now be made in detail to the present exemplary embodiments consistent with the invention, examples of which are illustrated in the accompanying drawings.

[0053] Customer purchase/return and fitting record is the foundation for this invention of fit prediction and wearable item recommendation. Figure 1A shows the data structure of a fitting record database, which consists of four components: Customer ID 110, Item ID 120, Date of Purchase 130 and customer Fitting Rating 140.

[0054] The present invention can work with or without fitting rating 140. Date of Purchase 130 is only used during testing, simulation, and fine-tuning of the present invention. It is evident in the present specification that Date of Purchase 130 is not necessary during actual use of the present invention.

[0055] "Customer" refers to the actual user of products, not necessarily the person who bought and paid for the product. Each customer will have a distinct customer ID, though the ID does not need to be related to the customer's real identity information.

[0056] "Item" refers to the products. "Item ID" identifies different products. Take footwear as an example, a distinct item ID refers to all shoes of a particular brand, in a particular function, of a particular model/style line, in a particular size, but can be any color. For example, Nike walking shoes for adult women's in the Nike Walker V model/style line, in size 6, in any color would have a distinct item ID. In other words, all shoes of the same item ID are exact the same in terms of fit characteristics and have the same item ID.

[0057] There are many existing product identification coding schemes for manufacturers, such as GTIN, UPC, or EAN. And retailers usually have their own SKU code scheme to manage inventory. It is better to use a widely-accepted coding scheme. If the coding system only identifies products brand and style but group all sizes together, a suffix can be added to identify different sizes. Generally speaking, manufacturers' coding schemes for production management and retailers' coding schemes for inventory management should be adequate for our purpose.

[0058] In this specification, lower-case letter i, j, k,…or number 1, 2, 3,… represent unique customers, and upper-case letter A, B, C,…, represent distinct wearable items. Each customer is assigned a unique customer ID. Each product item is assigned a distinct item ID as described above.

[0059] Customer purchase/return and fitting record can be recorded in a database. An example is shown in Figure 1A. There are 10 customers 1, 2, …,10; and 7 footwear items A,B,…, G. When a purchase is made, the date of purchase is recorded as shown: "08-1-2" means a purchase date of January 2nd, 2008. Again, Date of Purchase 130 is not needed to use the present invention.

[0060] Figure 1B contains the same data entries as Figure 1A, but arranged in a different manner to illustrate that a single customer makes multiple purchases and that a item is purchased by multiple customers.

[0061] For most online retailers, product return due to poor fit account for up to 1/3 of total items shipped. When a wearable item is purchased and returned, and not reason is given by the customer as to the reason of return, the corresponding purchase record entry should be deleted; when a wearable item is purchased and returned, and the customer has indicated the Fitting Rating, the corresponding purchase record entry should be preserved. In this specification, the word "purchase" means a corresponding purchase record entry is present in the database, not deleted.

[0062] The present invention requires only customer purchase/return records, although customer fitting ratings can be helpful.

[0063] Figure 1A and 1B are only shown for illustrative purpose. In actual implementation, this database will be very big. As an electronic database, with modern database programming techniques, there should be no difficulty in data

entry, management, or other standard database manipulations. This database can be constructed for different categories of wearable items, such as shoes, hats, gloves, upper-body clothing, pants, etc.

[0064] Forward search and reverse search are illustrated in Figure 2. The forward search starts from a customer i of customer set C 210 to find out all items he/she has purchased in item set D 220, which forms a sub-set D(i) 230. The reverse search starts from an item G of item set D 220 to find out all customers who have purchased item G, which forms a sub-set C(G) 240 in customer set C 210.

[0065] Figure 3 illustrates a forward search 310 starting from customer i resulting in a sub-set $D^1(i)$ 320 in item set D, followed by a reverse search 330 resulting in a sub-set $C^1(i)$ 340 in customer set C. Each customer j in $C^1(i)$ has purchased at least 1 same ID item as customer i. But more generally, any two customer j and k in sub-set $C^1(i)$ have not necessarily purchased same ID items. The superscript denotes the number of iteration of forward or reverse search.

[0066] Figure 4 illustrates a iterative forward and reverse search procedure 410 starting from customer i, which in successive iterations will result in sub-sets $D^1(i)$, $C^1(i)$, $D^2(i)$, $C^2(i)$, …, $D^k(i)$, $C^k(i)$, … As the process converges, we have $D^{n-1}(i)= D^n(i)$ and $C^{n-1}(i) = C^n(i)$. The search process is stopped when convergence occurs.

[0067] Although sub-set $C^n(i)$ is defined through a procedure starting from a particular customer i, there is nothing special about customer i. In fact, starting from any customer in $C^n(i)$ will result in the same sub-set $C^n(i)$. Hence $D^n(i)$ and $C^n(i)$ can be expressed as D_1 and C_1 respectively. The subscript “1” denotes the first subset found by the iterative process in customer set C and item set D.

[0068] Figure 5 illustrates part of the customers in sub-set C_1. Any two customer j and k in sub-set C_1 have not necessarily purchased same ID items, but could be indirectly connected through other customers. For example, customers 1 and 2 both purchased item A, customers 2 and 3 both purchased item B, customers 3 and 4 both purchased item C, etc.

[0069] Similarly, any two items A and K in sub-set D_1 have not necessarily been purchased by a customer, but could be indirectly connected through other items. For example, items A and B are both purchased by customers 1, items B and C are both purchased by customer 2, C and D are both purchased by customer 3, etc.

[0070] Starting from another customer j outside of sub-set C_1 and follow the same procedure we will get sub-sets C_2 and D_2. In the same way, sub-sets C_3 and D_3, C_4 and D_4,…can be found. It is evident that the intersection between any two sub-sets D_1, D_2, D_3,…, and between any two sub-sets C_1, C_2, C_3,…are all empty sets.

[0071] Taking the purchase record database in Figure 1A and 1B as an example, following a iterative forward and reverse search procedure starting from customer 1, we will get $D^1(1)=\{A, G\}$, $C^1(1)=\{1, 5, 8, 10\}$, $D^2(1)=\{A, B, G\}$, $C^2(1)=\{1, 5, 8, 9, 10\}$, after which the procedure converges; while starting from customer 2, we will get $D^1(2)=\{D\}$, $C^1(2)=\{2, 3, 6, 7\}$, $D^2(2)=\{C, D, E, F\}$, $C^2(2)=\{2, 3, 4, 6, 7\}$, after which the procedure converges.

[0072] The procedure divides the customer set C into two sub-sets $C_1=\{1, 5, 8, 9, 10\}$ and $C_2=\{2, 3, 4, 6, 7\}$ as illustrated in Figure 6. There are no common elements between C_1 and C_2.

[0073] In the same procedure the item set D is divides into two sub-sets $D_1=\{A, B, G\}$ and $D_2=\{C, D, E, F\}$ as illustrated by Figure 7. There are no common elements between D_1 and D_2.

[0074] Sub-sets C_1 and D_1, sub-sets C_2 and D_2 are mutually exclusive. This means that customers in C_1 have only purchased items in D_1, but not items in D_2, while customers in C_2 have only purchased items in D_2, but not items in D_1. The customer set and the item set are thus disjointed into sub-sets. Different body shapes lead to different wearable items purchased, and this would be beneficial to targeted marketing, wearable item recommendation, fit prediction and purchase records data self-correction.

[0075] Customers in a customer sub-set or items in an item sub-set can be further divided based on customers' Foot Shape Similarity and items' Specified Foot Shape Similarity as follows.

[0076] Foot Shape Similarity is used here as an example, it is understood that the concepts, principles and methods suggested here also can be applied to the similarity analysis on other parts of human body, such as head shape, hand shape, upper body shape, etc.

[0077] Foot Shape Similarity Degree of customers i and j is defined based on the fact that they have both purchased same ID shoes, which have the same fit

characteristics. For example, i and j both have purchased shoe A, then their foot shape are similar with each other to a certain extent, which can be expressed in a Foot Shape Similarity Degree. If, furthermore, i and j have both purchased another shoe B, Foot Shape Similarity Degree of i and j should be increased to reflect this new piece of evidence.

[0078] Foot Shape Similarity Degree is defined as a number between 0~1, or 0%~100%. The Foot Shape Similarity Degree between two customers gets a basic value of α while they both purchase first pair of same ID shoes; when they both purchase a different second pair same ID shoes, the Foot Shape Similarity Degree will increase, but not doubled; the different third purchase of same ID shoes results in a even smaller increment in Foot Shape Similarity Degree, and so on. For a particular value of α, the relation "Foot Shape Similarity Degree vs. The number of the same ID footwear items purchased" must be a kind of saturated curve as shown in Figure 8B. The reason for this saturation attribute lies in: a new piece of evidence of foot shape similarity is more valuable when the existing evidences are less. In fact, after the number of same ID shoes purchased by both customers reaches 6 or 7, Foot Shape Similarity Degree is very close to 100% and the further increase in the number of same ID shoes both purchased only leads to a negligible increase in Foot Shape Similarity Degree.

[0079] Figure 8A presents $S_{i,j}$, the value of Foot Shape Similarity Degree between customers i and j, when both customers purchased 1, 2, 3,…pair of same ID shoes under different values of α. The values of $S_{i,j}$, in the table are calculated by the following formula

[0080] $$S_{i,j} = 1-(1-\alpha)^n$$

[0081] Where, n is the number of same ID shoes both customers i and j purchased. The value of parameter α should be adjusted so that predicted return ratio, as described in Figure 24, coincides with actual return ratio. It is understood that above formula is only an example and any other formulae or methods may be used provided that the "Foot Shape Similarity Degree vs. The number of the same ID shoes purchased" curve is a kind of saturated curve.

[0082] Foot Shape Similarity Degree has the following attributes: $S_{i,i}$=100%, because anybody's foot shape is fully similar to him or herself; $S_{i,j}$=$S_{j,i}$, because the

similarity degree of customer i's feet to customer j's feet is equal to that of customer j's feet to customer i's feet.

[0083] Foot Shape Similarity Degree has transitive attribute. If customer 1 and customer 2 have similar foot shape, with a certain Foot Shape Similarity Degree between them and customers 2, 3 also have similar foot shape, with a certain Foot Shape Similarity Degree between them, it is reasonable to believe that customers 1 and 3 have similar foot shape to a certain extent. Based on the transitive attribute, even if two customers did not purchase same ID footwear hence their Foot Shape Similarity Degree cannot be calculated directly, their Foot Shape Similarity Degree can be calculated indirectly as shown in Figure 9:

[0084] 1. The indirect Foot Shape Similarity Degree takes the minimum value among all segmental Foot Shape Similarity Degree values along a serial route. As shown in Figure 9, customers 1 and 4 have never purchased same ID footwear and their foot shape similarity $S_{1,4}$ has to be calculated indirectly through $S_{1,3} \rightarrow S_{3,4}$, 510. Since $S_{1,3}$ and $S_{3,4}$ are 91% and 70%, respectively, so the smaller one should be taken and $S_{1,4}$=70%.

[0085] As shown in Figure 9, to calculate similarity degree $S_{1,4}$, besides the route $S_{1,3} \rightarrow S_{3,4}$ there exists another route $S_{1,2} \rightarrow S_{2,4}$, 520, which consists of 2 serial segments having Foot Shape Similarity Degree of 97.3% and 91% respectively, the smallest one should be taken as the indirect Foot Shape Similarity Degree $S_{1,4}$=91%.

[0086] 2. The indirect Foot Shape Similarity Degree takes the maximum value among all segmental Foot Shape Similarity Degree values among several parallel routes. As shown in Figure 9, the 2 parallel routes $S_{1,2} \rightarrow S_{2,4}$ and $S_{1,3} \rightarrow S_{3,4}$ have Foot Shape Similarity Degree of $S_{1,4}$=70% and $S_{1,4}$=91%, respectively, the larger one between them should be taken, so the final indirect Foot Shape Similarity Degree $S_{1,4}$=91%.

[0087] The indirect calculation of Foot Shape Similarity Degree is presented as an example. It actual implementation, there are other ways to make indirect calculation of Foot Shape Similarity Degree.

[0088] The Specified Body Shape Similarity Degree of wearable items, such as clothing, footwear or hat etc., can also be calculated based on customer purchase record. Once again Specified Foot Shape Similarity Degree is taken as an example.

All concepts, principles and methods described herein can also be applied to the similarity analysis of specified body shape of other kinds of wearable items.

[0089] As described above, customers having purchased same ID footwear must have some similarity in their foot shape, as measured by Foot Shape Similarity Degree. By the same token, footwear items purchased by the same customer must be similar with each other to some extent in their specified foot shape.

[0090] Specified Foot Shape Similarity Degree of footwear items is also calculated based on customer purchase records. As shown in Figure 1A and 1B, customer 1 has purchased both footwear A and G, which indicates that the specified foot shape of A and G are similar to some extent. When α = 0.8, we have Specified Foot Shape Similarity Degree of footwear A and G as $S^{A,G}$ =80%. Note that customer 10 has also purchased footwear A and G, which is one more piece of evidence that the specified foot shape of A and G are similar. Hence the Specified Foot Shape Similarity Degree of footwear A and G increases to $S^{A,G}$ =1-(1-0.8)^2=96%.

[0091] The values of Specified Foot Shape Similarity Degree between footwear A and G, when they are both purchased by 1, 2, 3,…customers, and under different values of α, are the same as shown in Figure 8A and 8B.

[0092] Specified Foot Shape Similarity Degree between footwear items and Foot Shape Similarity Degree between customers are highly symmetrical concepts. All attributes for Foot Shape Similarity Degree also apply for Specified Foot Shape Similarity Degree. The difference is Foot Shape Similarity Degree between two customers is derived from similarity analysis of purchased footwear by the two customers; while Specified Foot Shape Similarity Degree between two pairs of footwear is derived from similarity analysis of customers who purchased the two pairs of footwear.

[0093] Just as Foot Shape Similarity Degree can be calculated indirectly by the transitive attribute of Foot Shape Similarity Degree as shown in Figure 9, Specified Foot Shape Similarity Degree can also be calculated indirectly by the transitive attribute of Specified Foot Shape Similarity Degree. The process to calculate indirect Specified Foot Shape Similarity Degree is exactly the same as calculating indirect Foot Shape Similarity Degree aforementioned. The detailed steps are skipped because it should be evident to those skilled in the art.

[0094] Figure 10 presents an alternative method to calculate Specified Foot Shape Similarity Degree of footwear. There are two items of footwear A and B in item set D 1020, reverse searches form A and B result in sub-set C^A 1030 and C^B, 1040 in customer set C 1010 respectively. Suppose C^A = {i, j, …, k} and C^B = {i', j', …, k'}, which means customer i, j, …, k purchased footwear A, while customers i', j', …, l' purchased footwear B. And n customers purchased item A or B, and among them m customers purchased both A and B. Obviously, the higher the percentage of m/n, the more similar the Specified Foot Shape of A and B. From this we can define Specified Foot Shape Similarity Degree between footwear A and footwear B as $S^{A,B}$=m/n.

[0095] As defined in the preceding paragraph, Specified Foot Shape Similarity Degree $S^{A,B}$ is within 0~1, or 0%~100%. When the purchasers of item A and B are exactly the same, $S^{A,B}$=1, this means that the specified foot shape of A and B are the same; $S^{A,B}$=0 when the purchasers of A and B don't have any customer in common, this means that the Specified Foot Shape of A and B are entirely different.

[0096] Further, Foot Shape Similarity Degree $S_{i,j}$ of customers i and j can be derived from Specified Foot Shape Similarity Degree as defined above between all the shoes they have purchased. Even if customer i and j have not purchased any same ID shoes, their Foot Shape Similarity Degree can be derived as follows.

[0097] Suppose in purchase records of customers i and j include shoes A_1, A_2, …, A_i, …, A_n and B_1, B_2, …, B_j, …, B_m respectively. First, calculate Specified Foot Shape Similarity Degree of all the pair of $S^{Ai,Bj}$, and n×m Specified Foot Shape Similarity Degrees are obtained. Then the average $S_{i,j}$ of all $S^{Ai,Bj}$ is the Foot Shape Similarity Degree between customers i and j. The value of $S_{i,j}$ calculated as such is also within 0~1, or 0%~100%.

[0098] To put it another way, the average of all Specified Foot Shape Similarity Degrees between a piece of footwear purchased by customer i and another piece of footwear purchased by customer j is the Foot Shape Similarity Degree between customer i and j, where the Specified Foot Shape Similarity Degree is obtained by method illustrated in Figure 10. This is another method to calculate Foot Shape Similarity Degree indirectly.

[0099] Based on indirectly calculated Foot Shape Similarity Degree, more Foot Shape Similarity Degree can be obtained. In fact, among all the customers

connected by directly calculated Foot Shape Similarity Degrees, indirect similarity degree can be calculated between any two customers not connected by direct similarity degree. As shown in Figure 11, among 8 customers directly calculated Foot Shape Similarity Degrees are $S_{1,2}, S_{2,3}, S_{3,4}, S_{4,5}, S_{5,6}, S_{6,7}, S_{7,8}$ which are denoted by solid lines while the indirectly calculated Foot Shape Similarity Degrees are denoted by dotted lines.

[00100] A great variety of footwear items are available to consumers and the possibility for two customers to buy footwear of the same item ID is not always very high. Calculating indirect Foot Shape Similarity Degree greatly expends foot shape similarity relationships between customers.

[00101] The previously demonstrated analysis on customers' Foot Shape Similarity Degree leads to the concept of "Foot Shape Similarity Network". With regard to Body shape, this becomes "Body Shape Similarity Network". A "Foot Shape Similarity Network" corresponds to a "Customer Set" with Foot Shape Similarity Degrees calculated.

[00102] Corresponding to Figure 1A and 1B, the Foot Shape Similarity Network is shown in Figure 12 and Figure 6, where 10 customers are disjointed into two Foot Shape Similar Sub-Networks: 1, 5, 8, 9, 10 and 2, 3, 4, 6, 7. The Foot Shape Similar Degrees between any two customers in the same sub-network is determined by directly calculated similarity degrees, shown in solid line, or by indirectly calculated similarity degrees, shown in dotted line. Foot Shape Similar Degrees across sub-networks, however, can not be calculated because any customers of different networks have never purchased any same ID footwear. As a result, the network is disjointed into two sub-networks 1210 and 1220 as shown in Figure 12. The values of Foot Shape Similarity Degrees are also indicated in Figure 12.

[00103] Similarly, we have "Specified Foot Shape Similarity Network" as shown in Figure 13 and Figure 7, where the 7 footwear items from the database in Figure 1A and 1B are arranged and the Specified Foot Shape Similarity Degree between two items are expressed by lines, with full lines indicate directly calculated similarity degrees while dotted lines indicate indirectly calculated similarity degrees. The 7 items are obviously disjointed into two Specified Foot Shape Similarity Sub-Networks: A, B, G and C, D, E, F. The two Sub-Networks are separate because

there exists no Specified Foot Shape Similarity Degree relationship between their respective members. Specified Foot Shape Similarity Network displayed in Figure 13 is thus disjointed into two sub-networks 1310 and 1320 with solid lines represent directly calculated similarity degrees and dotted lines represent indirectly calculated similarity degrees. The values of Specified Foot Shape Similarity Degrees are also indicated in Figure 13.

[00104] Described above is an example on footwear. Generally speaking, all the customers in a purchase database, like the one shown in Figure 1A and 1B, for a particular category of wearable items, such as shoes, hats, gloves, upper-body clothing, pants, etc., can be expressed by a "Body Shape Similarity Network". Each network can be a Body Shape Similarity Network, or Foot Shape Similarity Network, or Head Shape Similarity Network, or Upper-body Shape Similarity Network, or Lower-body Shape Similarity Network, or Hand-shape Similarity Network, etc. The network can be disjointed into a number of sub-networks. The Body Shape Similarity Degree between any two customers across different sub-networks is 0, while any two customers in the same sub-network are connected by a Body Shape Similarity Degree, the value of which is greater than 0.

[00105] All the items in a purchase database, like the one shown in Figure 1A and 1B, for a particular category of wearable items can be expressed by a Specified Body Shape Similarity Network. The network can be disjointed into a number of sub-networks. Each sub-network is a Specified Body Shape Similarity Sub-Network. The Specified Body Shape Similarity Degree between any two items across different sub-networks is 0, while any two items in the same network are connected by a Specified Body Shape Similarity Degree, the value of which is greater than 0.

[00106] Further on the example on footwear, all the customers in a Foot Shape Similarity Sub-Network above described can be further divided into clusters according to their Foot Shape Similarity Degrees. The clustering method is as follows, as illustrated in Figure 14. To begin with any customer i 1410, search another customer j 1420 whose Foot Shape Similarity Degree with i S_{ij} is equal to or greater than a preset threshold, for example 0.8; then search for the third customer k 1430, whose Foot Shape Similarity Degrees with both i and j, S_{ik} and S_{jk} are both equal to or greater than 0.8; then search for the fourth customer l 1440, whose Foot Shape Similarity Degrees with i, j and k, S_{il}, S_{jl} and S_{kl} are all equal to or greater than

0.8…, and so on. Once the search cover the entire Foot Shape Similarity Sub-Network, cluster M_1={i, j, k, l,…} is obtained. Within this cluster, any two customers are connected by Foot Shape Similarity Degree equal to or greater than 0.8.

[00107] Although cluster M_1 is defined through a search procedure beginning with a particular customer i, there is nothing special about customer i. In fact, starting from any customer in M_1 will result in the same cluster M_1.

[00108] Starting from another customer in the Foot Shape Similarity Sub-Network but outside of M_1, another cluster M_2 is obtained. M_2 shares no common customers with M_1, i.e., the intersection of M_1 and M_2 is empty. It is easy to understand that if there is really a common customer in both M_1 and M_2 then it must have been included in M_1 when searching M_1's members. Furthermore, according to the transitive nature of similarity, as long as M_1 and M_2 have only one common customer then all the customers from M_1 and M_2 should have their similarity degrees equal to or higher than 0.8, and so M_1 and M_2 are effectively one cluster.

[00109] In the same way, we can find clusters M_1, M_2, M_3… etc. The Foot Shape Similarity Sub-Network is thus divided into disjointed clusters.

[00110] The threshold value 0.8 shown in Figure 14 is for illustrative purpose. It is adjustable in practice without departing from the principles of the present invention.

[00111] The foot shapes of all the customers in a Foot Shape Similarity Cluster are highly similar with each other, to an extent adjustable by the threshold value. A footwear item fit to one of them is likely fit to others in the cluster, and therefore, one customer's purchase record can be referenced by others in the same cluster.

[00112] In the same way, each Specified Foot Shape Similarity Network can be divided into a series of disjointed Specified Foot Shape Similarity Clusters N_1, N_2... etc.., each of them encompass of a number of footwear items highly similar, to an extent adjustable by the threshold value, with each other in terms of fit characteristics.

[00113] A particular cluster of footwear may include quite different footwear items belonging to different function lines, different brands, different styles or different colors; they are clustered into one sub-cluster because they are interchangeable. If one of them fits to a customer then very likely the other items in the same cluster would fit to the same customer, to a extent adjustable by the threshold value. While

the sizing standards of footwear are meant to standardize size across different brands, functional lines, and styles, in actuality a typical customer may find him/herself wear for example size 8 running shoes in one brand, size 8.5 dress shoes in another brand, etc. The clustering method proposed can cluster footwear and other wearable items in terms of fitting characteristics, not the nominal sizes.

[00114] Frequently, a shoe manufacturer will use the same series of shoe lasts, which represents the same specified foot shape, to make shoes in different model/style line and a clothing manufacturer will use the same measurements, or "cut", for different style of clothing. When such information is available from the shoe or clothing manufacturers, we can consider the different model/style shoes or clothing have the same fit characteristics for the purpose of fit prediction. In such cases, products of different item IDs can be grouped together and assigned the same item ID for fit prediction. However, even if that information was not available, the present invention will automatically cluster those shoes or clothing into the same clusters.

[00115] Figure 15A summarizes and clarifies the terms "Customer Set", "Sub-set", "Customer Network", "Sub-networks" and "Customer clusters". Customer Set 1511 contains all customers in the purchase record database. Through the iterative forward and reverse search 1514, Sub-Sets 1515 are discovered. When similarity degrees are calculated 1512, Customer Set 1511 becomes Customer Network 1513, and Sub-Sets 1515 become Sub-Networks 1516. The Sub-Networks 1516 are divided through clustering process 1517 into Customer Clusters 1518.

[00116] Take footwear as an example, the original Customer Set contains all customers in the purchase record database. Through the iterative forward and reverse search, Sub-Sets are obtained. Upon completion of similarity degree calculations, the Customer Set becomes Foot Shape Similarity Network and Sub-Sets become Foot Shape Similarity Sub-Networks. The Foot Shape Similarity Sub-Networks are divided into Foot Shape Similarity Clusters using a preset similarity degree threshold. Other categories of wearable items follow the same process.

[00117] Figure 15B summarizes and clarifies the terms "Item set", "Item Sub-set", "Item Network", "Sub-networks" and "Item clusters". Item Set 1521 contains all items in the purchase record database. Through the iterative forward and reverse search

1524, Sub-Sets 1525 are discovered. When similarity degrees are calculated 1522, Item Set 1521 becomes Item Network 1523, and Sub-Sets 1525 become Sub-Networks 1526. The Sub-Networks 1526 are divided through clustering process 1527 into Item Clusters 1528.

[00118] Take footwear as an example, the original Item Set contains all footwear in the purchase record database. Through the iterative forward and reverse search, Sub-Sets are obtained. Upon completion of similarity degree calculations, the Item Set becomes Specified Foot Shape Similarity Network and Sub-Sets become Specified Foot Shape Similarity Sub-Networks. The Specified Foot Shape Similarity Sub-Networks are divided into Specified Foot Shape Similarity Clusters using a preset similarity degree threshold. Other categories of wearable items follow the same process.

[00119] If not only customer purchase records but also their fitting ratings are available, then similarity analysis on customers' body shape and items' specified body shape can be corrected to produce more accurate predictions and recommendations.

[00120] As an example, Figure 16 is customers' fitting rating form for footwear items. The customer will pick a Fitting Rating for a footwear item after actual try on. The database will assign the corresponding Fit Score. The scores represent departures of footwear's specified foot shape from customers' foot shape. To a certain extent, the absolute value of the scores reflects the extent to which the footwear item fit or doesn't fit a customer.

[00121] The Fitting Ratings and Fit Score values shown in Figure 16 are for illustrative purpose. It is adjustable in practice without departing from the principles of the present invention.

[00122] Figure 17 shows that customers' fitting ratings can be used to calculate minor difference between body shapes and to refine their Body Shape Similarity Degrees. The following description uses footwear as an example.

[00123] As shown in Figure 16, customers' fitting rating on the fit, tight or loose, of a footwear item is ranked in 9 levels of Fit Score: -0.4, -0.3, -0.2, -0.1, 0.0, 0.1, 0.2, 0.3, 0.4, with an increment between levels of 0.1. In Figure 17, suppose purchase record shows that customers i and j 1720 both have purchased footwear G 1710,

which means their foot shapes are similar to a certain degree. However, if the fitting ratings 1730 on the fit of footwear G from the two customers are different, there exist some Minor Difference d_{ij}^{G} 1740 between their foot shapes. Customer i's rating e_i is "Excellent" (score: 0) while j's rating e_j is "tight" (score:-0.2), this means that j's foot is larger than i's foot by 2 levels: $e_i - e_j = 0-(-0.2) =0.2$. As another example, customer i's rating e_i is "Very tight" (score:-0.3) while j's rating e_j is "Very loose" (score: 0.3), this means that j's foot shape is smaller than i's foot shape by 6 levels: $e_i^G - e_j^G = -0.3-(0.3))= -0.6$. If the two customers both purchased footwear G, P, …, Q, then according to their fitting ratings to each footwear item the Minor Differences between their foot shapes can be worked out as $d_{i,j}^{G}$, $d_{i,j}^{P}$, …, $d_{i,j}^{Q}$, and the average $d_{i,j}$ of these values is the overall Minor Difference between foot shapes of customers i and j, which indicates that j's foot is larger than i's foot by $d_{i,j}$. If $d_{i,j} < 0$, then j's foot is smaller than i's foot. Obviously, $d_{i,j}$ is skew symmetric, where $d_{i,j}=-d_{j,i}$.

[00124] Based on Minor Difference, the Foot Shape Similarity Degree between two customers can be corrected. The principle is: if customers i and j both have purchased footwear G, then their Foot Shape Similarity Degree is $s_{i,j}^{G}=1-(1-\alpha)=\alpha$ according to the method previous described. If the Minor Difference $d_{i,j}^{G}$ 1740 is taken into consideration, then the corrected Foot Shape Similarity Degree between the two customers must be reduced to $cs_{i,j}^{G}=1-(1-(\alpha-|d_{i,j}^{G}|))= s_{i,j} - |d_{i,j}^{G}|$,where "c" indicates "corrected" and "$|\cdot|$" denotes absolute value. If the two customers both have also purchased footwear P, and we have worked out Minor Difference $d_{i,j}^{P}$, then the corrected Foot Shape Similarity Degree is $cs_{i,j}^{G,P}=1-(1-(\alpha-|d_{i,j}^{G}|))(1-(\alpha-|d_{i,j}^{P}|))$. If the two customers both have purchased a series of footwear G, P, …, Q, then corrected Foot Shape Similarity Degree is:

[00125] $$cs_{i,j} =1-(1-(\alpha-|d_{i,j}^{G}|))(1-(\alpha-|d_{i,j}^{P}|))\ldots(1-(\alpha-|d_{i,j}^{Q}|)).$$

[00126] There is a simplified method of calculating corrected Foot Shape Similarity Degree:

[00127] $$cs_{i,j} = 1-\left(1-(\alpha-|d_{i,j}|)\right)^{n}$$

[00128] Corrected Foot Shape Similarity Degree $cs_{i,j}$ = 0~1, if α is assigned a value of no less than 0.8. Generally, Foot Shape Similarity Degree $cs_{i,j}$ is between 0 and 1 if α is greater than the maximum range of fit score. As shown in Figure 16, the maximum range of fit score is 0.4-(-0.4)=0.8 in this example.

[00129] Figure 18 shows that customers' fitting ratings can also be used to calculate Minor Difference between specified body shapes of wearable items and to correct Specified Body Shape Similarity Degrees. The following description uses footwear as an example.

[00130] In Figure 18, suppose purchase record shows that customer i 1810 has purchased both footwear G and footwear P 1820. The specified foot shape of G and P are similar to a certain degree. However, if the fitting ratings e_i^G and e_i^P 1830 on fit of footwear G and P from customers i are different, then there exist some Minor Difference d_i^{GP} 1840 between the specified foot shape of G and P. Customer i's rating on footwear G is "Excellent" (score: 0) while on P is "tight" (score: -0.2), this means that P's specified foot shape is smaller than G's specified foot shape by 2 levels: $d_i^{GP} = e_i^P - e_i^G = -0.2 - 0 = -0.2$. As another example, customer i's rating on G is "Very tight" (score: -0.3) while on P is "Very loose" (score: 0.3), this means that P's specified foot shape is larger than G's specified foot shape by 6 levels: $d_i^{GP} = e_i^P - e_i^G = 0.3-(-0.3)) = 0.6$. If the two footwear items have both been purchased by customers i, j, …, k, then according to the fitting ratings of all the customers to footwear G and P, Minor Difference between the specified foot shape of these two items can be worked out as $d_i^{G,P}$, $d_j^{G,P}$, …, $d_k^{G,P}$, and the average $d^{G,P}$ of these values is the overall Minor Difference between the specified foot shape of items i and j, which indicates that P's specified foot shape is larger than G's specified foot shape by $d^{G,P}$. If $d^{G,P} < 0$ then P's specified foot shape is smaller than G's specified foot shape. Obviously, $d_{G,P}$ is skew symmetric, where $d^{G,P} = -d^{P,G}$.

[00131] Based on Minor Difference, the Specified Foot Shape Similarity Degree of two footwear items G and P can be corrected. The principle is: if footwear G and P have both been purchased by customers i, then their Specified Foot Shape Similarity Degree is $s_i^{G,P} = 1-(1-\alpha) = \alpha$, according to the method previous described. If the Minor Difference $d_i^{G,P}$ is taken into consideration, then the corrected Specified Foot Shape Similarity Degree between the two items must reduced to $cs_i^{G,P} = 1-(1-(\alpha-|d_i^{G,P}|)) = s_i^{G,P}-|d_i^{G,P}|$. If customer j have also purchased both footwear G and P, and we have worked out Minor Difference $d_j^{G,P}$, then the corrected Specified Foot Shape Similarity Degree must be $cs_{i,j}^{G,P} = 1-(1-(\alpha-|d_i^{G,P}|))(1-(\alpha-|d_j^{G,P}|))$. If the two items have both been purchased by a series of customers i, j, …,k, then corrected Specified Foot Shape Similarity Degree must be

[00132] $cs^{G,P} = 1-(1-(\alpha-|d_i^{G,P}|))(1-(\alpha-|d_j^{G,P}|))\ldots(1-(\alpha-|d_k^{G,P}|))$.

[00133] There is a simplified method of calculating corrected Specified Foot Shape Similarity Degree:

[00134] $$cs^{G,P} = 1-\left(1-(\alpha-\left|d^{G,P}\right|)\right)^n$$

[00135] Corrected Specified Foot Shape Similarity Degree $cs^{G,P}$ = 0~1, if α is assigned a value of no less than 0.8. Generally, $cs_{G,P}$ is between 0 and 1 if α is greater than the maximum range of fit score. As shown in Figure 16, the maximum range of fit score is 0.4-(-0.4)=0.8 in this example.

[00136] It is understood that the fit ratings, fit scores and the parameter α presented here are for illustrative purpose only. During implementation, these values can be adjusted without departing from the principles of the present invention.

[00137] The difficulties and inconvenience of actually trying on wearable items can be greatly reduced or eliminated by “virtual try on”.

[00138] Figure 19 demonstrates an example of “virtual try on” of footwear. Suppose customer i, 1910 is attracted by a style X 1920 of footwear while browsing website, catalogs or in a shop window. But customer i does not know the exact size suitable and doesn’t want to try, or cannot as in the case of online shopping. In this case the proper size can be recommended based on the present invention. The method can be described as follows: search the sizes of footwear style X purchased by customers belonging to the same Foot Shape Similarity Cluster 1930 as customer i. If p customers 1, 2, … , p are found having purchased footwear style X, the sizes are m_1^X, m_2^X, …, m_p^X respectively, and the Foot Shape Similarity Degree of each of those customers with respect to customer i are known as S_{i1}, S_{i2}, …, S_{ip} respectively, then the weighted average of m_1^X, m_2^X, …, m_p^X with S_{i1}, S_{i2}, …, S_{ip} as the weights is likely the right size of footwear G for customer i to purchase. The average should be rounded to a nearest standard size.

[00139] If the conversion relations among different size schemes or different size standards are known, the experience of those customers, who have similar foot shape with customer i, i.e. belonging to the same cluster, but purchased footwear style P, Q, …, R, other then style X, also can be used for customer i’s reference. In

this case, the sizes m_1^P, m_2^Q, …, m_p^R for those footwear should be converted to style X's sizes m_1^X, m_2^X, …, m_p^X before weighted-average calculation.

[00140] Figure 20~23 illustrate four examples of fit prediction methods for wearable items. As customer i intend to purchase footwear item G, the following methods can be applied to predict the fit of G to i, without actual try on.

[00141] Figure 20: Search all the footwear items A, B, …, F 2030 customer i 2010 has purchased and the Specified Foot Shape Similarity Degrees of those items with respect to G 2020 are $S^{A,G}$, $S^{B,G}$, …, $S^{F,G}$, then the average of these values indicates the Fit Score f_i^G of item G to customer i.

[00142] Figure 21: Search all the customers j, k, l,…, o 2130 who have purchased item G 2120 and the Foot Shape Similarity Degree of them with respect to i 2110 are $S_{i,j}$, $S_{i,k}$, …, $S_{i,o}$, then the average of these values indicates the Fit Score f_i^G of item G to customer i.

[00143] The above two methods are based on only customer purchase records and result in a number f_i^G =0~1, the bigger the value f_i^G the better the fit quality of item G to customer i's foot shape.

[00144] If the customers' fitting ratings are available, then the Fit Score, which is the degree of tight or loose as expressed in Figure 16 can be predicted more accurately.

[00145] Figure 22: Search all the footwear items A, B, …, F customer i has purchased. The Fit Scores of customer i on these items are e_i^A, e_i^B, …, e_i^F 2210, and the specified foot shape Minor Differences of items A, B, …, F with respect to item G are $d^{A,G}$, $d^{B,G}$,…,$d^{F,G}$ 2220. These Minor Differences are calculated from the Fit Scores of those customers who have purchased item G and one or more items among items A, B, …, F. Suppose the Fit Score of i on A is e_i^A=0.2, which is Acceptable Fit and loose, and the Minor Differences of specified foot shape of G with respect to A is $d^{A,G}$=0.1, which means G is bigger than A by 0.1level. From these facts a solution can be derived: the rating of i on G must be $e_i^{G\leftarrow A}=e_i^A+d^{A,G}$=0.2+0.1=0.3, which means Unacceptable Fit and Very loose, the upper index "G←A" indicates that the rating is indirectly derived through the Fitting Rating of i on A. Similarly, $e_i^{G\leftarrow B}=e_i^B+d^{B,G}$,…, $e_i^{G\leftarrow F}=e_i^F+d^{F,G}$, 2230. The weighted average $e_i^G=f_i^G$ of $e_i^{G\leftarrow A}$, $e_i^{G\leftarrow B}$,…, $e_i^{G\leftarrow F}$ 2240 is the predicted Fit Score of i on G. The

weights are $cs^{G,A}$, $cs^{G,B}$,…,$cs^{G,F}$ 2250, which are the corrected Specified Foot Shape Similarity Degree of each of A, B, …, F with respect to G.

[00146] If any derived Fit Scores $e_i^{G\leftarrow A}$, $e_i^{G\leftarrow B}$,…, $e_i^{G\leftarrow F}$ exceeds the range of Fit Score, which is -0.4~0.4 in this example, such derived Fit Scores should be discarded in the weighted average calculation. The derived Fit Scores must be within the range set for original Fit Scores.

[00147] This is an indirect method. Customer i has not tried on footwear G, so his/her Fitting Rating on item G can not be known directly. However, it is possible to derive i's rating on G indirectly through i's Fit Score e_i^A, e_i^B, …, e_i^F on items A, B,…,P, which Customer i has purchased, and the Minor Differences $d^{A,G}$, $d^{B,G}$,…,$d^{F,G}$ of G with respect to each of A, B,…,F.

[00148] Figure 23: Search all the customers j, k, …, l who have purchased item G. The Fit Scores of these customers on item G are e_j^G, e_k^G, …, e_l^G 2310. the corrected Foot Shape Similarity Degree of each of these customers with customer i are $cs_{i,j}$, $cs_{i,k}$, …, $cs_{i,l}$. The foot shape Minor Difference of customer i with respect to each of these customers are $d_{j,i}$, $d_{k,i}$, …, $d_{l,i}$ 2320. Similar as described in Figure 22, the Fit Score of customer i on footwear G can be derived. $e_{i\leftarrow j}^G=e_j^G+d_{j,i}$, $e_{i\leftarrow k}^G=e_k^G+d_{k,i}$, …, $e_{i\leftarrow l}^G=e_l^G+d_{l,i}$ 2330. The weighted average $e_i^G=f_i^G$ of $e_{i\leftarrow j}^G$, $e_{i\leftarrow k}^G$,…, $e_{i\leftarrow l}^G$ is the predicted rating of i on G 2340. The weights are $cs_{i,j}$, $cs_{i,k}$, …, $cs_{i,l}$ 2350.

[00149] If any derived Fit Scores $e_{i\leftarrow j}^G$, $e_{i\leftarrow k}^G$,…, $e_{i\leftarrow l}^G$ exceeds the range of Fit Score, which is -0.4~0.4 in this example, such derived Fit Scores should be discarded in the weighted average calculation. The derived Fit Scores must be within the range set for original Fit Scores.

[00150] This is an indirect method. Customer i has not tried on footwear G and his/her Fitting Rating on item G. However, it is possible to derive i's rating on G indirectly through customers j, k, …, l's Fit Score e_j^G, e_k^G, …, e_l^G on G, and the foot shape Minor Differences $d_{j,i}$, $d_{k,i}$, …, $d_{l,i}$ of these customers with respect to i.

[00151] The above two methods are based on customer purchase records and customer Fitting Ratings, The f_i^G will have the same range as Fit Score, which is -0.4~0.4 in this example.

[00152] The above four methods are presented as examples to adequately disclose the present invention. Variations and modifications can be made without departing from the principles of the present invention.

[00153] Product return is mainly due to bad fit. As the Fit Score of footwear item G to a particular customer i can be predicted without actual try on, there is no difficulty in predicting the possibility of returning of an item purchased.

[00154] Return rate of wearable G by a customer i, or the possibility of return, r_i^G can be expressed in a simple relation to the Fit Score e_i^G:

[00155] $r_i^G=\lambda e_i^G$, when $e_i^G \geq 0$； and $r_i^G=-\beta e_i^G$, when $e_i^G<0$.

[00156] The value of $\lambda, \beta>0$, but the value of λ and β have to be determined by actual return rate. Generally, $\beta>\lambda$, because the average customer is less tolerate to "tight" than "loose" fit.

[00157] Figure 24 shows an example, demonstrating the relations between e_i^G and r_i^G. As an example, $\lambda=2$, $\beta=2.5$. The shaded areas, $e_i^G<-0.24$ or $e_i^G>0.3$, represent cut-off return rate $r_i^G>60\%$. Transactions fall under such areas should be avoided to control return rate.

[00158] The preceding example is for illustrative purpose only. The value of λ and β and the cut-off return rate are adjustable without departing from the principles of the present invention.

[00159] Figure 25 summarizes the present invention, showing its components and processes. The system consists of 3 main blocks: The Customer Purchase Record Database 2510, The Algorithm & Program 2520, and The Customer Services 2530.

[00160] The Customer Purchase Record Database block 2510 includes a Basic Database 2511, customers' Fitting Rating and Fit Score Database 2512, and Data of Purchase 2513. The Basic Database includes Customer ID, Item ID.

[00161] Data of Purchase 130 is only used during testing, simulation, and fine-tuning of the present invention. It is evident in the present specification that Data of Purchase 130 is not necessary during actual use of the present invention.

[00162] In The Algorithm & Programs block 2520, following an iterative forward and reverse search 2541 starting from arbitrarily selected customers, the Customer Set and the Item Set are divided into disjointed Sub-Sets 2521.

[00163] Within a Customer Sub-Set, between any two customers, calculate customer Body Shape Similarity Degrees 2551 to obtain Body Shape Similarity Degrees 2522. Within an Item Sub-Set, between any two items, calculate Specified Body Shape Similarity Degrees 2552 to obtain Specified Body Shape Similarity Degrees 2523

[00164] When available, starting from Customers' Fitting Rating & Fit Score Database 2512, calculate Minor Differences 2542 to obtain Minor Difference between customers' Body Shapes or Specified Body Shapes of wearable items 2524.

[00165] Take into account Minor Differences 2542, calculate Corrected Similarity Degrees 2555, Body Shape Similarity Degrees 2522 is adjusted 2553 toward corrected Body Shape Similarity Degrees 2525. Take into account Minor Differences 2542, calculate Corrected Similarity Degrees 2555, Specified Body Shape Similarity Degrees 2523 is adjusted 2554 toward corrected Specified Body Shape Similarity Degrees 2525.

[00166] With corrected Similarity Degrees 2525, Body Shape Similarity Network and Specified Body Shape Similarity Networks 2526 are obtained through 2529. Sub-Networks 2526 are also obtained based on similarity connections.

[00167] The Body Shape Similarity Sub-Networks and Specified Body Shape Similarity Sub-Networks 2526 are divided into smaller clusters based on a threshold of similarity degree 2556. Body Shape Similarity Clusters of customers and Specified Body Shape Similarity Clusters of items 2527 are obtained.

[00168] The Customer Services block 2530 includes Virtual Try On: Item Size Recommendation 2531, Fit Prediction of a Wearable Items to a Customer 2532; Prediction of Product Return and Return Ratio Control 2533FIG. 1 illustrates an embodiment of a 20. The

[00169] Although the steps of the method of operating the system 20 are listed in a preferred order, the steps may be performed in differing orders or combined such that one operation may perform multiple steps. Furthermore, a step or steps may be initiated before another step or steps are completed, or a step or steps may be initiated and completed after initiation and before completion of (during the performance of) other steps.

[00170] The preceding description has been presented only to illustrate and describe exemplary embodiments of the methods and systems of the present invention. It is not intended to be exhaustive or to limit the invention to any precise form disclosed. It will be understood by those skilled in the art that various changes may be made and equivalents may be substituted for elements thereof without departing from the scope of the invention. In addition, many modifications may be made to adapt a particular situation or material to the teachings of the invention without departing from the essential scope. Therefore, it is intended that the invention not be limited to the particular embodiment disclosed as the best mode contemplated for carrying out this invention, but that the invention will include all embodiments falling within the scope of the claims. The invention may be practiced otherwise than is specifically explained and illustrated without departing from its spirit or scope. The scope of the invention is limited solely by the following claims.

CLAIMS

WHAT IS CLAIMED IS:

1. A method comprising:

identifying an ordering customer and a desired wearable item;

identifying a body shape similarity cluster correlating to the ordering customer;

identifying at least one comparable customer belonging to the same body shape similarity cluster as the ordering customer, wherein each comparable customer has purchased at least one wearable item belonging to the same style, same brand and same size schemes as the desired wearable item;

identifying the size of at least a portion of the wearable items purchased by comparable customers;

identifying a body shape similarity degree for at least a portion of the comparable customers with respect to the ordering customer;

calculating a recommended size value for the desired wearable item suitable to the ordering customer.

2. The method of claim 1, wherein the size value for the desired wearable item is calculated as a weighted average of the sizes of all the wearable items purchased by comparable customers in the same style, same brand and same size series as the desired wearable item and with body shape similarity degrees for each comparable customer with respect to the ordering customer as weights.

3. The method of claim 1, wherein one of the comparable customers may be the ordering customer, wherein the ordering customer has purchased at least one wearable item in the same style, same brand and same size series as the desired wearable item.

4. The method of claim 1, further comprising determining a body shape similarity degree between the comparable customer and the ordering customer on the basis of purchase/return records.

5. The method of claim 1, wherein the identification of the desired wearable item includes identification of the brand and the style of the desired wearable item.

6. The method of claim 1, further comprising compiling a database of body shape similarity degrees that correlate to at least a portion of the comparable customers and the ordering customer.

7. The method of claim 1, further comprising calculating a body shape similarity degree between at least a portion of the comparable customers and the ordering customer.

8. The method of claim 1, further comprising providing a fit recommendation for the ordering customer that correlates to the desired wearable item.

9. A method comprising:

identifying an ordering customer and a desired wearable item;

identifying at least one wearable that is associated with the ordering customer, wherein the ordering customer has tried on at least a portion of the identified wearable items; and

identifying at least one similarity between each of the identified wearable items and the desired wearable item.

10. The method of claim 9, further comprising obtaining an estimated fit score for the desired wearable item with respect to the ordering customer.

11. The method of claim 10, wherein fit score is the average of a plurality of specified body shape similarity degrees of the plurality of wearable items associated with the desired wearable item.

12. The method of claim 9, further comprising obtaining a plurality of fit scores of the plurality of wearable items that are associated with the ordering customer, wherein the ordering customer has assigned a fit score to at least a portion of the plurality of wearable items.

13. The method of claim 12, further comprising using at least a portion of the plurality of fit scores associated with the plurality of wearable items to calculate the estimated fit score.

14. A method comprising:

identifying an ordering customer and a desired wearable item;

identifying a plurality of comparable customers that are associated with the desired wearable item, wherein at least a portion of the comparable customers have tried on the desired wearable item; and

identifying at least one substantially similar fit characteristic between each of the comparable customers and the ordering customer.

15. The method of claim 14, further comprising obtaining an estimated fit score for the desired wearable item with respect to the ordering customer based upon, at least in part, a body shape similarity degrees.

16. The method of claim 15, wherein obtaining the estimated fit score includes averaging the body shape similarity degrees of the wearable item with respect to each of the comparable customers.

17. The method of claim 14, further comprising obtaining a plurality of fit scores of the desired wearable item that are associated with the comparable customers, wherein at least a portion of the comparable customers have each assigned a fit score to the desired wearable item.

18. The method of claim 14, further comprising using at least a portion of the plurality of fit scores associated with the desired wearable item to calculate the estimated fit score.

19. The method of claim 14, wherein identifying a plurality of comparable customers includes accessing a computer readable medium.

110 Date of Purchase	120 Customer ID	130 Item ID	140 Fitting Rating
07-01-23	3	D	
07-01-28	4	C	
07-03-24	7	F	
07-04-01	5	B	
07-04-13	3	C	
07-05-03	2	D	
07-06-15	9	B	
07-07-23	10	A	
07-08-05	6	D	
07-08-28	4	F	
07-09-22	5	A	
08-01-02	1	A	
08-01-25	7	D	
08-02-21	6	F	
08-02-29	3	E	
08-03-01	10	G	
08-03-04	1	G	
08-03-12	8	G	

Figure 1A

	A	B	C	D	E	F	G
1	08-01-02						08-03-04
2				07-05-03			
3			07-04-13	07-01-23	08-02-29		
4			07-01-28			07-08-28	
5	07-09-22	07-04-01					
6				07-08-55		08-02-21	
7				08-01-25		07-03-24	
8							08-03-12
9		07-06-15					
10	07-07-23						08-03-01

Figure 1B

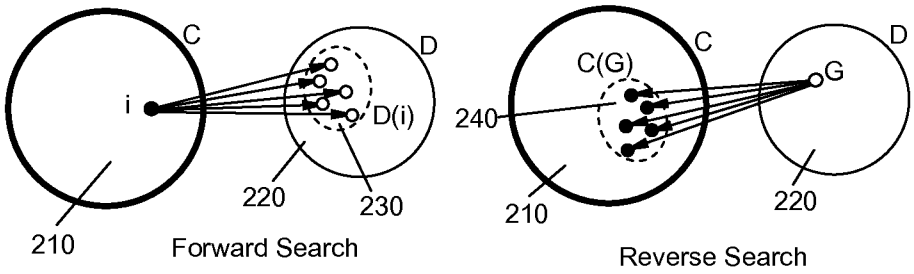


Figure 2

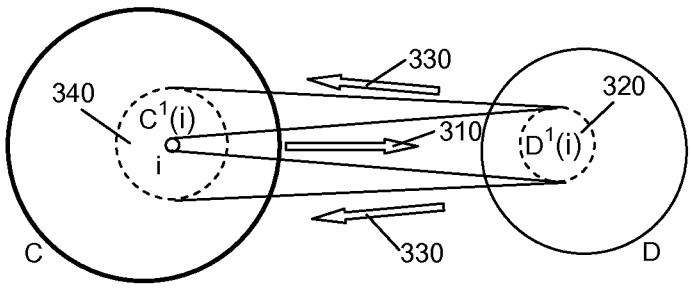


Figure 3

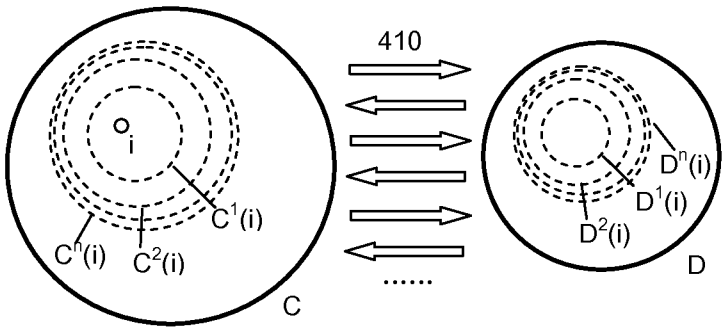


Figure 4

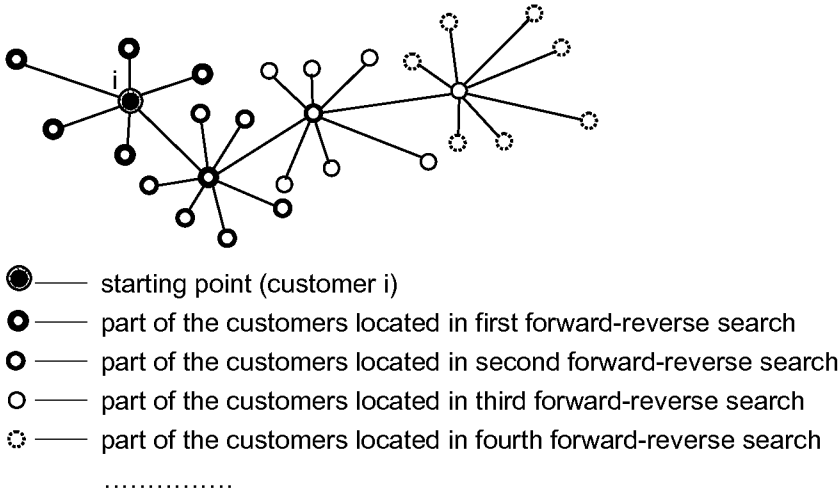


Figure 5

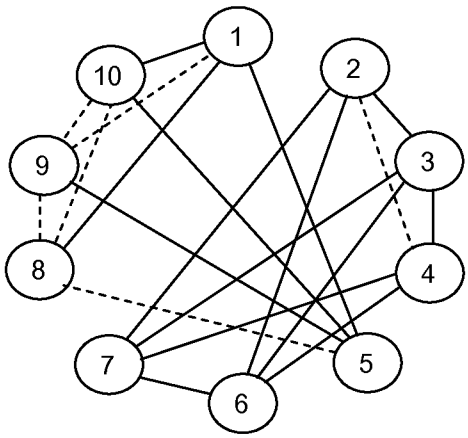


Figure 6

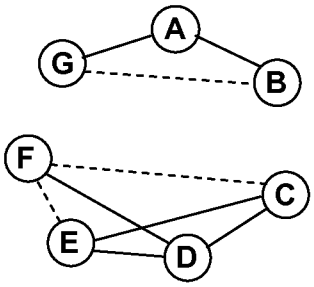


Figure 7

Foot Shapes Similarity Degree (%) between two customers, under different α

values and the number of pairs of same ID footwear purchased, n.

α \ n	1	2	3	4	5	6	7	8	9	10
0.5	50.00	75.00	87.50	93.75	96.88	98.44	99.22	99.61	99.80	99.90
0.6	60.00	84.00	93.60	97.44	98.98	99.59	99.84	99.93	99.97	99.99
0.7	70.00	91.00	97.30	99.19	99.76	99.93	99.98	99.99	100.00	100.00
0.8	80.00	96.00	99.20	99.80	99.97	99.99	100.00	100.00	100.00	100.00
0.9	90.00	99.00	99.90	99.99	100.00	100.00	100.00	100.00	100.00	100.00

Figure 8A

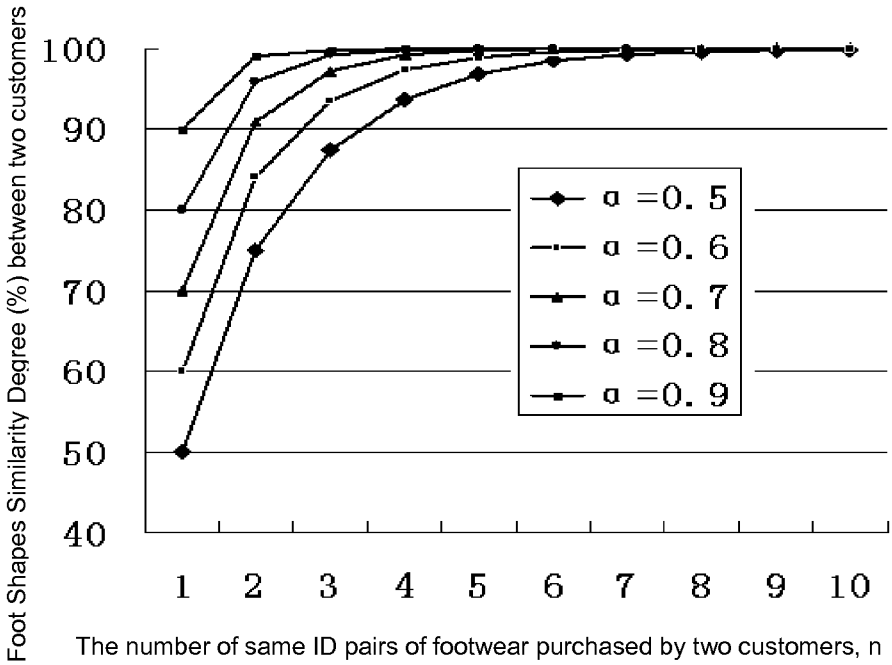


Figure 8B

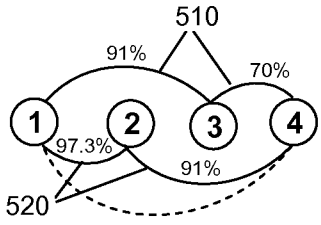


Figure 9

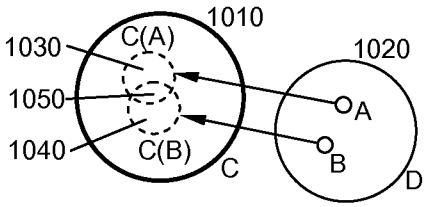


Figure 10

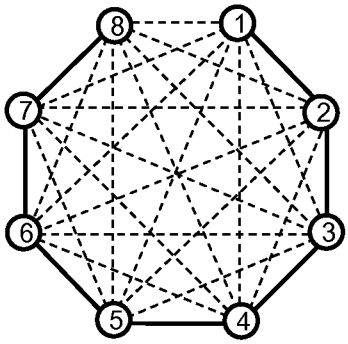


Figure 11

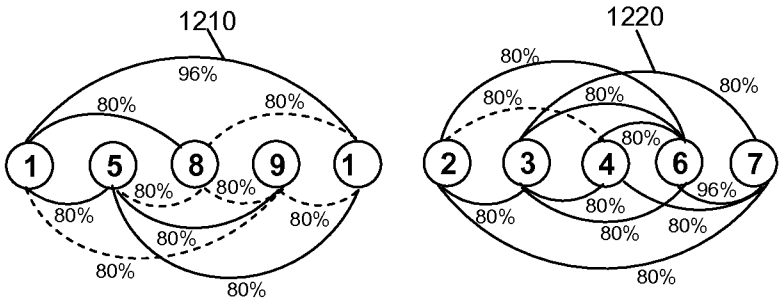


Figure 12

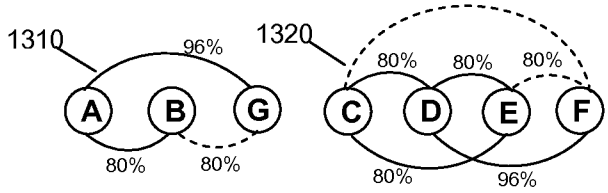


Figure 13

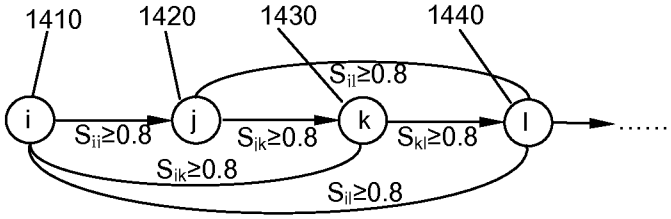


Figure 14

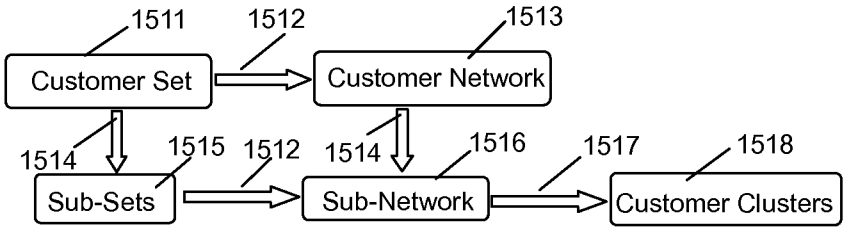


Figure 15A

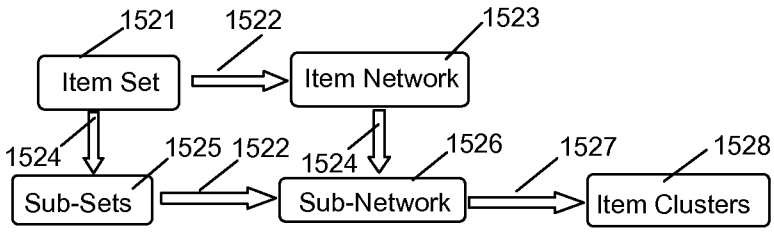


Figure 15B

Fitting Rating (Customer Feedback)	Fit Score (Assigned by Database)
Excellent Fit □	0.0
Good Fit	
Slightly Tight □	-0.1
Slightly Loose □	0.1
Acceptable Fit	
Tight □	-0.2
Loose □	0.2
Unacceptable Fit	
Very Tight □	-0.3
Very Loose □	0.3
Worst Fit	
Extremely Tight □	-0.4
Extremely Loose □	0.4

Figure 16

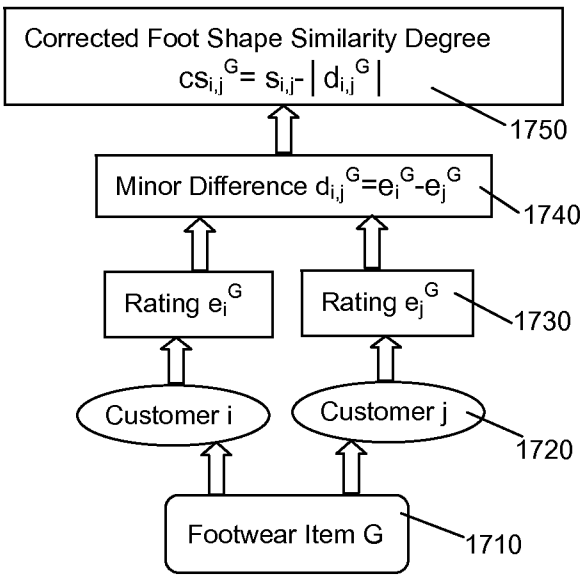


Figure 17

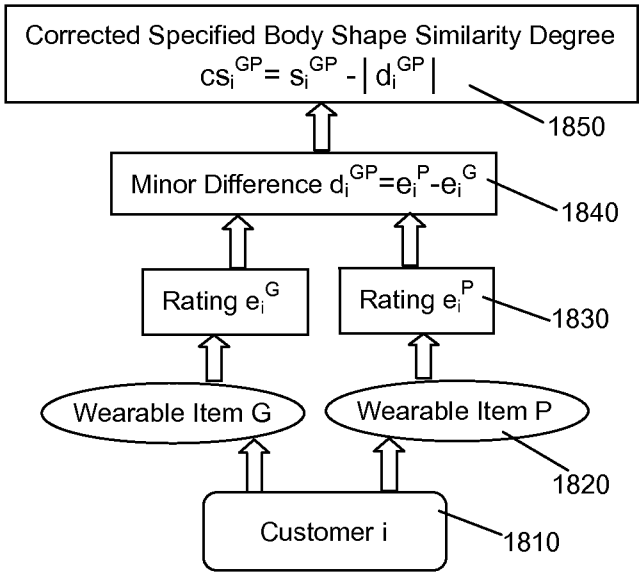


Figure 18

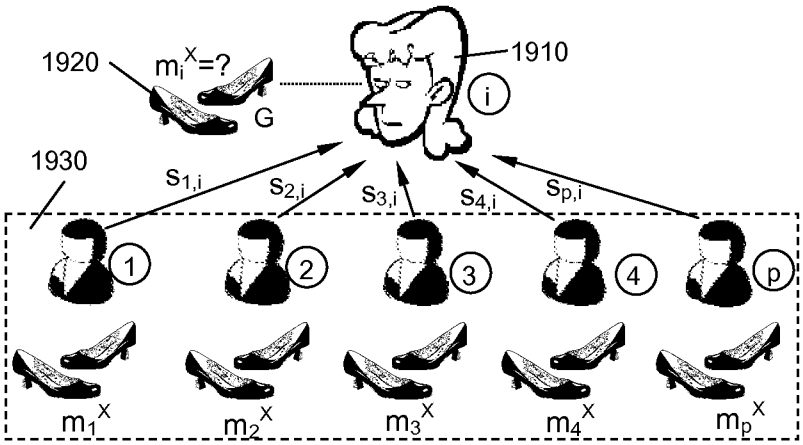


Figure 19

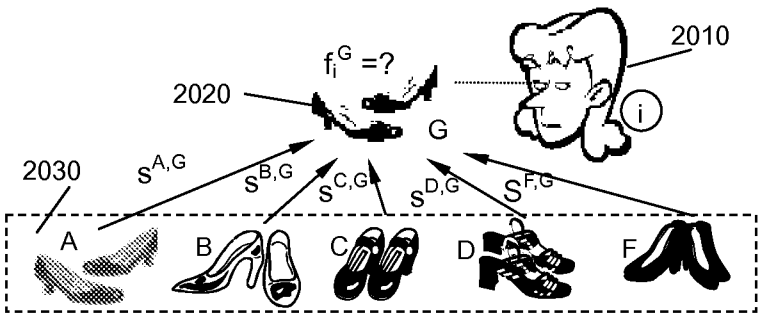


Figure 20

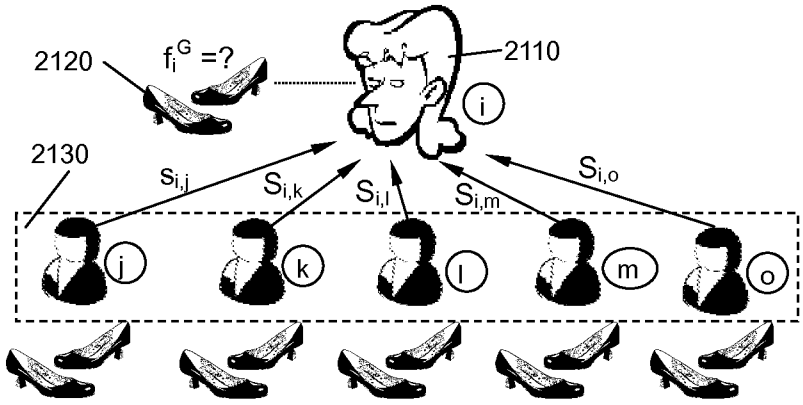


Figure 21

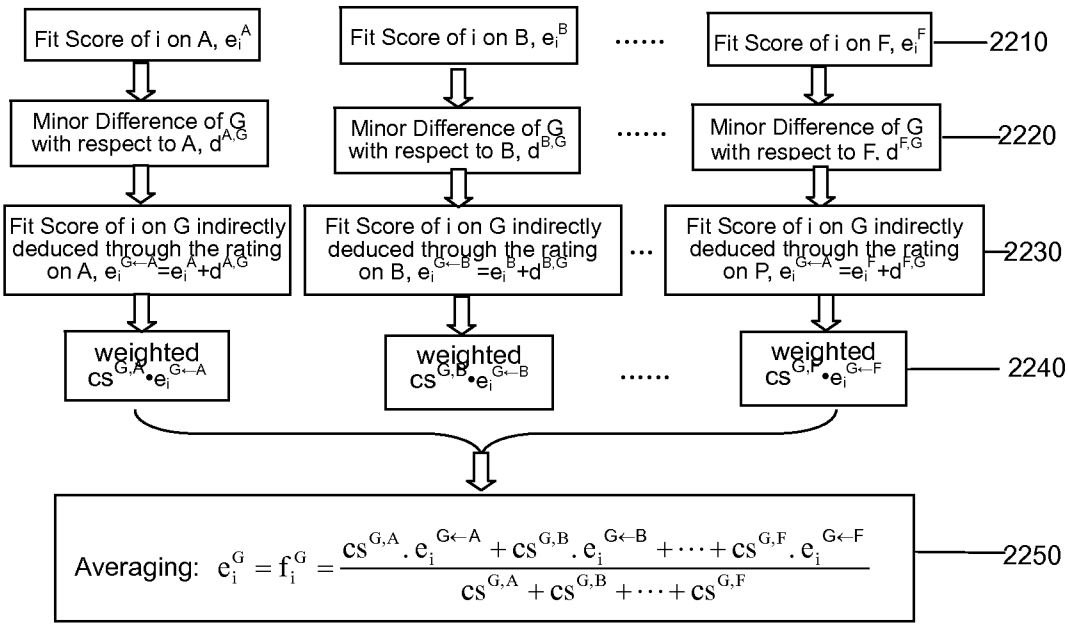


Figure 22

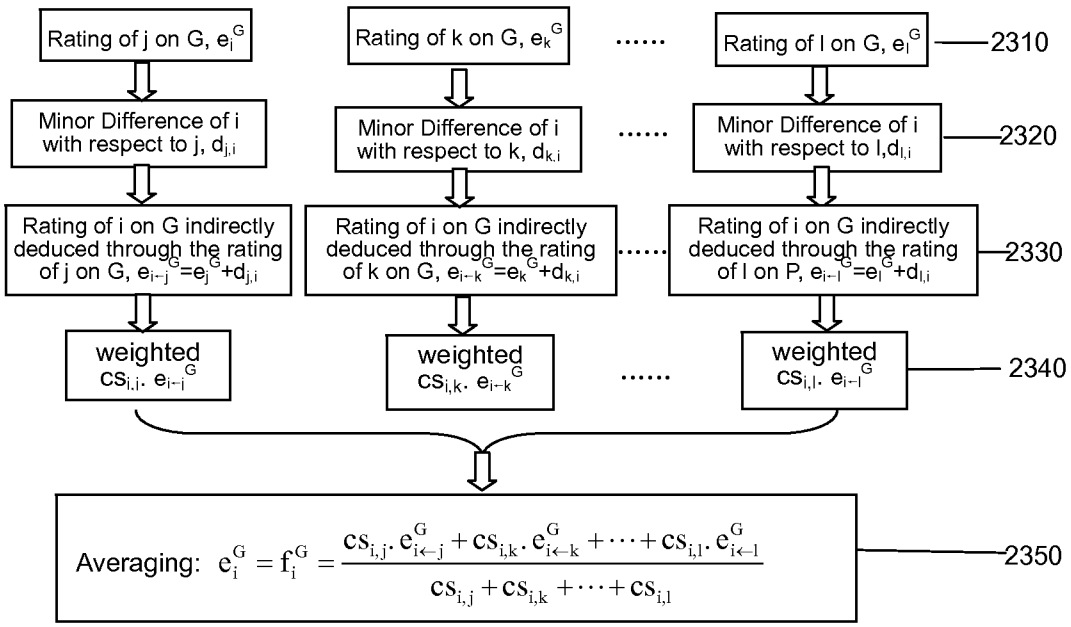


Figure 23

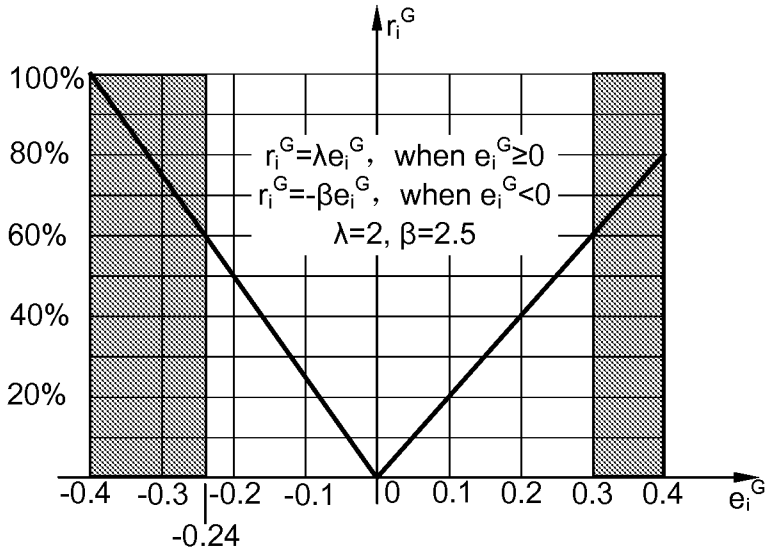


Figure 24

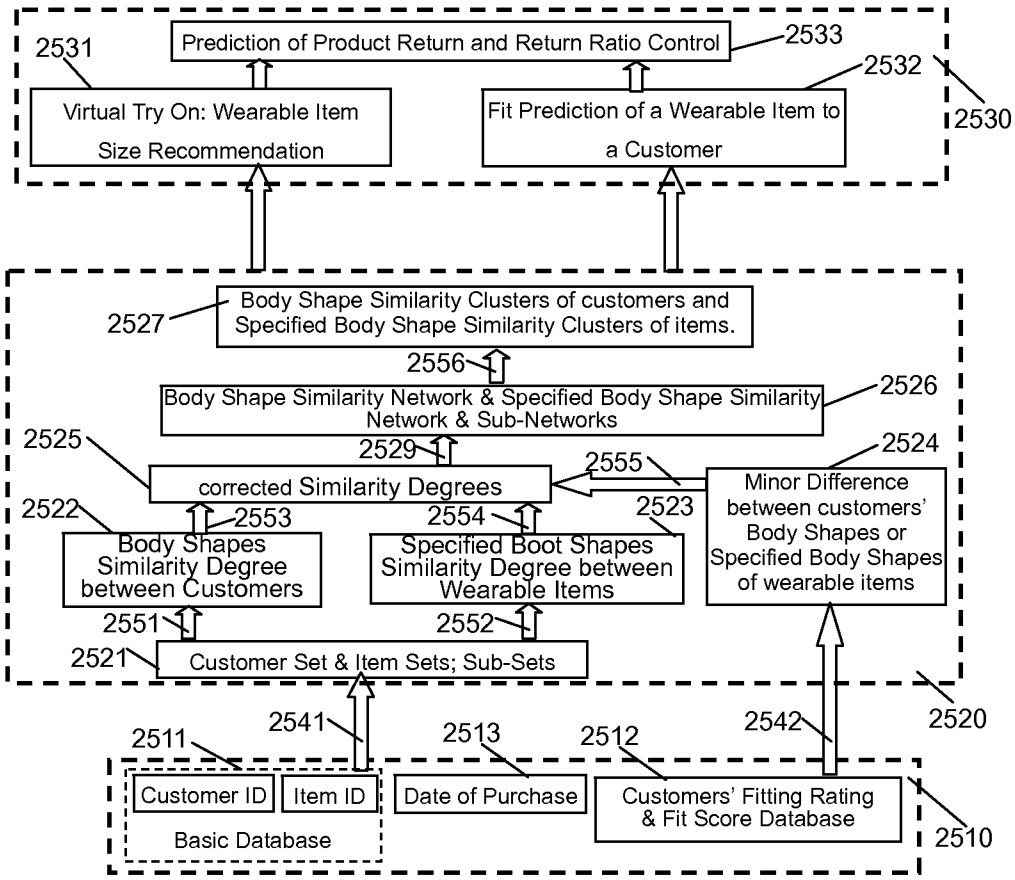

2531
Prediction of Product Return and Return Ratio Control
2533
2532
Virtual Try On: Wearable Item Size Recommendation
Fit Prediction of a Wearable Item to a Customer
2530
2527
Body Shape Similarity Clusters of customers and Specified Body Shape Similarity Clusters of items.
2556
Body Shape Similarity Network & Specified Body Shape Similarity Network & Sub-Networks
2526
2525
2529
2555
2524
corrected Similarity Degrees
Minor Difference between customers' Body Shapes or Specified Body Shapes of wearable items
2522
2553
2554
2523
Body Shapes Similarity Degree between Customers
Specified Boot Shapes Similarity Degree between Wearable Items
2551
2552
2521
Customer Set & Item Sets; Sub-Sets
2520
2541
2542
2511
2513
2512
Customer ID
Item ID
Date of Purchase
Customers' Fitting Rating & Fit Score Database
Basic Database
2510

Figure 25