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A new data structure and workflow for using 3D anthropometry in the design of wearable products

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Abstract.

The human body is a complex biomechanical system that exhibits many variations. Wearable products should be both functional and comfortable. They require a close and accurate fit to the body of the end-user. Current approaches to design body near products rely on 1D anthropometry and unrealistic manikins, e.g. constructed from simple surfaces such as spheres and cylinders connected by splines. With the uprising of 3D scanning, a myriad of accurate 3D body models becomes available. In this paper we present a framework to use this 3D shape information in the development of wearable products. The key concept that we introduce to achieve this extension, is an enriched shape model: a statistical shape model of the human body that also contains all 1D anthropometric data in it. With enriched shape models, a 3D shape can be parameterized with a given set of anthropometric features. Thus the dense geometric information of an individual's shape can be obtained simply by tuning that individual's anthropometric values. By designing on the generated 3D surface, a product can be obtained that closely fits the individual's shape. We thus extend the method of linking 1D anthropometric data with the dimensions of a product. This results in three design strategies that link both body shape with product geometry: design for collective fit, design for fit within clusters and design for individual fit. Each strategy is explained and studied with the design of wearable EEG headsets that fits the human head.

Keywords

Mass-customization, EEG headsets, CAD, parameterized design, 3D anthropometry, statistical shape models

Relevance to Design Practice

We present a workflow to use accurate 3D shape models of the human body in the design of products that should closely fit the end-user. To that end, we introduce enriched shape models: a new data structure that contains all dense geometric shape information together with classical anthropometric data. We illustrate how enriched shape models can be used to achieve products with personalized fit, as an extension to the use of univariate anthropometric data. The use of enriched shape models for personalized design could become an important driver for mass customization. To that end, tools and techniques should be developed to incorporate the presented workflow in CAD/CAM.

1. Introduction

Anthropometry is used in the process of industrial design to cope with variations between humans with the aim to optimize products for fit, comfort, functionality and safety (1). The human body exhibits many variations, both in size and in shape. Consumer products that have a close fit with the human body often require full 3D models of the human body or body parts.

Companies that develop head mounted products such as helmets, headgear, glasses and headphones are interested in new tools and techniques to incorporate realistic and accurate head models in their design process (2-4). Also in the design of protective clothes and safety equipment, sports equipment, and for the development of medical and orthopedic products, there is a need for accurate descriptions of the shape variations of the human body (5) (6, 7) (8). These efforts and needs show that the sparse geometric information contained in 1D anthropometric data is not adequate enough to ensure proper fit, comfort and functionality.

With 3D scanning, dense and detailed geometric information of the human body can be captured. Technological advances in image capturing devices (e.g. 3D scans, cameras, computercam, Kinect, smartphone), medical imaging (CT and MRI scans), image processing software (9), allow for construction large databases of 3D body shapes. Realistic static 3D images of the human body are increasingly available over the past decade (10) (11) (12). With the alignment of international 3D anthropometrical databases (13), a realm of realistic 3D models of the human body is potentially constructed (14). Data acquisition is regulated by ISO 20685:2010. This norm can be targeted by convenient 3D scanners (15), so the amount of 3D data is expected to increase even further. 3D anthropometry is an emerging field with great potential for industrial design (16). Accurate 3D body data in digital form might be useful for optimizing product comfort and function (17). The merits of new tools to deploy true body models directly in the process of industrial design are clearly demonstrated (3). For the moment, they are confined to one specific design on one specific manikin. The question arises how parameterized designs can be constructed that directly adapts to a subjects 3D anthropometry, in an intuitive, smart and efficient way.

The purpose of this paper is to present a data structure that contains the full geometric complexity, intrinsic organic nature (variable radii of curvature) and variation in human body shape and that allows a practical and user-friendly workflow for the design of wearable products. In the next section (Section 2) we present three design strategies that link 1D anthropometric data with product dimensions: design for collective fit, design for fit within clusters and design for individual fit. The aim of each strategy is to define products whose dimensions are aligned the dimensions of the target population. Then, in Section 3, we explain how each of these three strategies can be extended to a new design strategy. The three new design strategies link accurate 3D models of the human shape with the entire product surface geometry, to achieve a fit between product and surface shape.

Digital design tools have been developed to apply these new design strategies on the human head. In Section 4 we present three design cases as a proof of concept for each design strategy. The human head is particularly suited to study these new workflows, because of its relevance in industrial design practice and the static, geometric nature (3). Results are discussed in Section 5 and concluded in Section 6.

2. Linking body sizes to product sizes

Traditional 1D anthropometrical data are numbers that represent body dimensions. Their statistical

distribution is univariate, by definition. It is straightforward to link such data on human sizes with the dimensions of a product, or vice versa (18, 19) (20).

There are established and straightforward design strategies for applying 1D anthropometry in the design process to take account of that variation throughout the target population. These design strategies all exploit the fact that direct relations can be defined between product dimensions and body parameters and are well integrated in the design process (20, 21). The univariate character of 1D anthropometric data ensures that it can be linked to product dimensions. The fact that these data represent physical parameters ensures that they can be retrieved in a practical life context.

Consequently, design strategies can be defined to determine proper product size. The first strategy is a design for collective fit or design for the average (22), or a design for all, where a single solution is adapted such that it is usable for the whole population (23). The second strategy is a design for fit within cluster strategy that is derived from achieving fit by considering percentiles (1) and overlaps of percentiles. The last strategy is an approach where the design is tailored to a subject's individual sizes.

2.1 Design for collective fit

A first design strategy that we consider is *design for collective fit*. The dimensions of a new product are pinpointed such that only one product size can fit the entire target population. Often, mean, median, percentiles or extreme measures are relevant parameters for a design base in this approach. Variations throughout the target population are coped within the design, e.g. by material characteristics, such as flexible temples to achieve universal fitting sun-glasses, or by adjustable elements e.g. (universally fitting) folding bike optimization (24). A contemporary example is the design of a bicycle that can be shared (25, 26), meeting trends and opportunities for improved and cleaner traffic (26, 27).

This design strategy potentially yields a sub-optimal fit for some subgroups.

2.2 Design for fit within clusters

A second strategy is to *design for fit within clusters*. Thereby the domain of the target population is clustered to minimize variation in size in each part. The design problem to achieve proper fit is thus reduced to finding a proper fitting design for each cluster. Each sub-problem is thus equivalent to a design for collective fit for the target population restricted to the respective cluster. Cluster specific measures such as cluster mean, -median and -extremes are relevant parameters for a design base in this approach.

For example, for the purpose of bicycle design, the domain of the target population is usually first split up along gender (m/f). This first variability is coped with offering different designs for men and women. Then populations are clustered and frame sizing systems are defined according to the developers experience and available information (28) (29).

2.3 Design for individual fit

A third design strategy is to *design for individual fit*. This means that the dimension of the product are completely tuned to the individual sizes of one particular end user. If 1D body data is directly

connected to the dimension of a product, it suffices to alter the dimensions accordingly to achieve an individual fit. Such examples can be found in personalized bike fitting, e.g. to achieve maximal comfort (30).

3. Enriched statistical shape models: from 1D to 3D anthropometry

A statistical shape model (SSM) is a collection of similar forms in which each form is described with a common parameter domain. For each shape, this is a one-to-one parameterization such that a correspondence between similar points is established (31, 32). Research on statistical shape models of the human body has made major progress, with over the last decades the seminal work of Allen to establish correspondences (33), construction of the Caesar database (10, 11) and a realm of 3D databases becoming available (13). Applications comprise animations (34, 35), apparel (6, 36, 37), orthopedics (8) and industrial design (7, 16, 17, 38, 39). Where in traditional anthropometry, shape is described by a set of 1D measurements using several univariate statistical distributions, SSMs directly describe the whole 3D shape using a single multivariate, high-dimensional distribution. Due to the abstract nature of this distribution, it is challenging to use SSMs in the design process (3).

The core of a statistical shape model is formed by on one hand a collection of similar forms and on the other hand a correspondence between them. That correspondence is far from unique. The same collection of similar forms can correspond in many different ways. Statistical shape models of the human body can thus be constructed under a variety of constraints. In particular, a statistical shape model of the human shape can be constructed such that a given set of anatomical landmarks is preserved. These are points on the human body that are consistently identified by varying operators in varying subjects, either manually by sensing, visually or geometrically by measuring aids (40).

We define an **enriched statistical shape model** (enriched SSM) as a shape model that preserves a certain set of anthropometric landmarks. Anthropometrical data that is geometrically inferred from anatomical landmarks, is also contained in the enriched SSM.

An enriched SSM can be constructed from a collection of 3D scans along three steps. Firstly, all relevant landmarks are annotated on the scans, meaning that each landmark is at the same anatomical location on each of the shapes, e.g. at the tips of the nose or eyes, see Figure 1. Secondly, a landmark preserving correspondence between each of these 3D scans is constructed by either a conformal mapping from a parameter domain (41) or by registering each 3D scan onto a template model (42). Each shape can thus be represented as a large but fixed number of points or vertexes, say $((x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_M, y_M, z_M))$, concatenated such that respective points (x_i, y_i, z_i) and (x'_i, y'_i, z'_i) of any two shapes correspond.

Figure 1: A collection of 3D models. Each of these heads is represented with 10.000 points, with an example of corresponding anatomical locations denoted with red, green and yellow dots.

Any shape is thus represented by M concatenated vertex coordinates. For a population of N shapes, this results in a cloud of N points in a $3M$ -dimensional space, a highly dimensional ‘shape space’. Thirdly, the cloud of shapes is modeled by a multidimensional distribution, e.g. by the application of principal components analysis (PCA). This results in an average shape and a set of ‘principal’ shape variations, mutually orthogonal in the highly dimensional shape space by construction. Variation throughout the target population (tensor Frobenius norm) can be visualized as a heat map on the average form, see Figure 2, left.

Figure 2: Left: mean shape of a population of 100 3D head scans color coded with the amount of variations. Right: visualisation of the first three principal shape modes of the population after PCA analysis, shown from three viewpoints (anterior, cranial, and lateral). The shape mode is visualised as an offset to the mean surface: the red surface is a negative offset and the white surface is a positive offset, each at three standard deviations along the distribution of principal component weights-which are assumed to be Gaussian.

Although a SSM provides a complete and mathematically elegant description of the population, it is cumbersome to work with for product designers. This is because the principal shape modes describe variation only in a highly dimensional abstract space, and not in terms of measurable real world parameters that could be used as a basis for a design equation or other intuitive controls.

The key property of *enriched* SSMs is that one can reverse the extraction of 1D data from a 3D shape: a best matching 3D form can be calculated by matrix algebra from a given set of 1D data (43).

The **feature map** of an enriched SSM is defined as the assignment of a collection of anthropometric values to its best matching shape. Our proposition is that this feature map-the construction of 3D body models from features- is a key property for making enriched SSM's available for designers. The feature map of enriched SSMs can be used to extend the three strategies presented above. It allows incorporating 3D anthropometry in the design process in a clear intuitive and user-friendly way.

3.1 Enriched SSMs for collective fit

Design for collective fit starts from a mean body shape, with anthropometric landmarks and/or anthropometric curves to inoculate the design. Variations can be mapped with a heat-map representing the spatial variations at each point, or with a vector field drawn at the surface indicating mean direction of variation and the length representing dispersion? These can , eventually restricted to normal direction, or displayed with ghost surfaces e.g. the surfaces representing the 5 and 95 percentile of the first principal component as in Figure 2, right. These tools can provide designers with visual clues and objective 3D information to cope more effectively with shape variations and construct better fitting products.–

3.2 Enriched SSMs for fit within clusters

Design for fit within clusters starts with clustering the target population with a dissimilarity metric (44). The purpose is to minimize dissimilarity between elements within the same cluster (45). In each cluster, a representative manikin can be picked. This is usually the center, mean or medoid along the dissimilarity metric. Enriched SSMs allow three clustering methods that are of interest in product development (46).

Feature based clustering is obtained by defining clusters in a space of 1D anthropometric features. The dissimilarity metric is obtained from 1D anthropometric data and/or other features, as explained in (47). Data can be deduced from classical measurements or retrieved from enriched SSMs. In the latter the representative manikin is a 3D shape too. Note that clustering with only one feature coincides with traditional 1D anthropometric clustering, yielding clear univariate sizing systems e.g. head circumference as in (2). We say that a cluster is shaped as a (generalized) square if it is completely defined by its edges, where all edges are line segments. Square shaped clusters allow for a *sizing system*: an individual is assigned to its cluster by simply checking if each feature is in the respective line segment. Note that an individual can belong to more than one sizing system, because two clusters can overlap. If clusters are non-overlapping, the assignment of a subject to its cluster is

unambiguous. Through the feature map, one can provide a best fitting shape for each set of feature values in a cluster. Thereof one can calculate the mean 3D shape for that cluster, or extreme 3D shapes, or shapes that corresponds to percentiles of features. A disadvantage of feature based clustering is that it discards the full dense geometric dissimilarity between 3D shapes.

Shape based clustering is constructed from a dissimilarity metric that takes account of the whole shape, as proposed for footwear design (7). For the purpose of clustering, regular dissimilarity metrics between shapes $A=((x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_M, y_M, z_M))$ and $A'=((x'_1, y'_1, z'_1), (x'_2, y'_2, z'_2), \dots, (x'_M, y'_M, z'_M))$ are weighted Manhattan/sum or Euclidean metric resp.

$$d_s(A, A') = 1/M \sum_{i=1}^M |x_i - x'_i| + |y_i - y'_i| + |z_i - z'_i| \text{ and}$$

$$d_E(A, A') = 1/M (\sum_{i=1}^M |x_i - x'_i|^2 + |y_i - y'_i|^2 + |z_i - z'_i|^2)^{1/2}$$

From a mathematical point of view it might be most suited to work with d_E since this metric nicely behave with respect to computational methods (48). From a design point of view two other dissimilarity metrics could be considered:

$$d_{E, \text{sum}}(A, A') = 1/M \sum_{i=1}^M (|x_i - x'_i|^2 + |y_i - y'_i|^2 + |z_i - z'_i|^2)^{1/2}$$

$$d_{\text{max}}(A, A') = \max_{i=1}^M (|x_i - x'_i|^2 + |y_i - y'_i|^2 + |z_i - z'_i|^2)^{1/2}$$

The first metric expresses the average Euclidean distance between corresponding points. The second metric expresses the magnitude of any possible variation that might occur between the shapes A and A' . A design that copes with d_{max} dissimilarity together with body-to-product tolerances, ensures perfect fit.

A disadvantage is that shape based clusters offer no rules to assign an individual to its closest corresponding clusters in terms of 1D anthropometric values. One could consider the square hull of each cluster to define such an assignment, but then an overlap in hulls will be created, introducing ambiguity in the assignment.

Feature-constraint shape based clustering resolves this by clustering based on 3D dissimilarity as explained above, each cluster subject to the restriction to be shaped as a generalized square. This results in non-overlapping squared clusters, with a clear sizing system to assign an individual to its cluster.

3.3 Enriched SSMs for individual fit

The feature map of an enriched SSM can be used to generate parameterized body models with less effort than current 3D scans. Such parameterization provides a dense description of 3D shape but then related to 1D anthropometric data. The potential arises to construct a design equation in terms of these parameters, tightly fitting the resulting shape. In such a setting, the design could be altered by tuning the 1D anthropometric values without any additional effort. For a given set of 1D values, variation within the envelope of all shapes with these values can be mapped, e.g. as a heat map on the best fitting shape (43, 49) (49). This variation displays the accuracy of the feature map. The accuracy increases as the number of features increases.

4. Linking body shapes to product shapes

An enriched SSM of the human head was retrieved from medical images, preserving fourteen common head landmarks by construction, as denoted in Figure 3: glabella (g), ophistocranion (op), left and right ektokanthia (ek1 and ek2), both otobasia (obi1 and obi2), both tragi (t1 and t2), sub-aurola (sba), super aurola (sa), inion (i), nasion (n), subnasal (sn) and vertex (v). These results are retrieved from digital models in which correspondence is group-wise optimized to achieve maximal compactness (50). It was found that only four parameters: head length (HL), bitragion width (BW), head circumference (HC) and arc length (AL), suffices to predict the skull with average spatial accuracy of about 1.64 mm and standard deviation of 0.4 mm (43).

Figure 3: anatomical measurements of the skull used to predict 3D skull form: head length (HL), bitragion width (BW), head circumference (HC) and arc length (AL) of the head and respective anatomical landmarks (43).

The feature map for these four parameters is further used to provide a proof of concept for the design of wearable products, in each of the three design strategies explained above. The wearable product we consider is an EEG headset (51). We have chosen for the human head for the static nature of this body part, for the concentration of applications around the head, and for the fact that the complex geometry of the head poses particular design challenges in head mounted products (3). We have chosen to explain the design strategy with the design of an EEG headset since there are particular anthropometric challenges in the design of comfortable and wearable EEG headsets (51). Electrodes should make proper contact at standardized anatomical locations that are geometrically derived from nasion, inion and left and right preauricular points, along the 10-20 system (52). As these four points correspond by construction (43) and electrode position were derived geometrically thereof, it can be assumed that these locations correspond as well. This assumption was confirmed on a few samples.

4.1 A case on collective fit

Fourteen electrode positions used in commercial BCIs as in (53) are AF3, AF4, F7, F3, F4, F8, FC5, FC6, T7, T8, P7, P8, O1, O2, circled in orange in Figure 4, left. These positions were constructed for each model in the enriched SSM, directional variations of these points along the first principal component were mapped (Figure 4, middle) on mean head shape and used for a straightforward one-size-fits-all non-functional EEG headset prototype (Figure 4, right).

Figure 4: electrode locations as used in commercial BCIs (left), average head with 5-95 percentile along the first principal component as ghost surfaces, points of interests displaying directional variation along this principal component, and the resulting non-functional prototype (54).

This design has 10% improvement in electrode positions and repeatability compared to commercially available BCI headsets (54).

4.2 A case on fit within clusters

A feature-constrained shape based clustering of the human scalp was performed. The number of clusters was set to three, yielding clusters say A, B, C. An EEG headset was defined targetting the same fourteen electrode locations as the one-size fits all design. A design equation on one cluster medoid and transferred to the two other cluster medoids using the correspondences of the enriched SSM. Cluster medoids, corresponding designs and prototypes are displayed in Figure 5.

Figure 5: Medoid head shapes for a feature-constrained clustering in three clusters (top), respective EEG designs (middle) and a prototype on a subject (bottom).

Inter-cluster variation was anticipated by placing sponges at electrode locations and by the flexibility of the polymer of the 3D prints. The design is considerably more straightforward in geometrical complexity compared to the one-size fits all. Clustering allows material reduction, omitting the need to cope with complex spatial variations compared to the one-size fits all design presented above and commercially available BCIs (53).

4.3 A case on individual fit

The feature map of the enriched SSM constructed in (43) was implemented in a user-friendly online tool that is locally hosted by the authors. Head shapes (.stl files) are generated by either numerical or percentile values for nine 1D measurements including HL, BW, HC and AL, shown in Figure 6.

Figure 6: online tool to generate head models from feature values and percentiles.

An EEG headset was constructed in a collaboration between the University of Antwerp and design and engineering company Pilipili. A test subject for personalized design was selected by Pilipili. Then a practical method to retrieve 1D anthropometric values HC, AL, BW and HL was defined in four steps. Firstly, instructions were given to Pilipili for measuring HC, AL, BW and HL with visuals and a brief description how to take these measures (Figure 11, first row). Secondly, the subject's measurements were assessed by Pilipili along these instructions. Arc length features HC and AL were provided numerically whereas linear straight measures were provided graphically by taking front and profile photographs of the subject's head and a ruler (Figure 7, second row). Thirdly, 1D values were extracted by UA from these graphics and substituted in the online tool that

executes the feature map. This generates a digital model of the subject's head. Fourthly, the head model was supplied to Pilipili that has used it as a design basis (Figure 7, fourth row).

Figure 7: Design for individual fit. Visual instructions for taking head measurements HC, AL, BW and HL (first row), executed (second row) to serve as input for feature map to generate a model (third row) for the design of a BCI headset (forth row).

The design fits remarkably well on the subject's head, with all electrodes making proper contact.

5. Discussion

Tools and techniques are needed to deploy the realm of statistical shape models in product development (55). Shape models are already used for this purpose for more than a decade (33). In all cases, a 3D model is generated for one product and one target group, such as e.g. manikins for helmets for the Chinese population (2, 3) or manikins for trousers (5). The problem is that the construction of such manikins is expensive in terms of labor, time and computational resources. Even the tailored EEG headset that we presented, was not transferred to any other individual's shape, but rather used in one size for different users. But with enriched SSMs and the presented ways to use them, we have introduced a formal data structure and workflow that can be implemented in CAD/CAM. Such a tool has the potential to leverage many disadvantages of ergonomic design based on 1D anthropometry.

5.1 Potential for collective fit

In design for collective fit based on 1D anthropometry, taking account of only one parameter in 1D anthropometry or one-dimensional information often yields sub-optimal results towards fit and comfort. This is also the case if the workflow is based on manikins that are defined as

straightforward geometrical constructions in function of that 1D data. Improvements in fit and comfort can be expected using enriched SSMs. This was indeed shown in the design of a one-size-fits-all BCI concept (54).

5.2 Potential for fit within clusters

Some disadvantages concerning the 1D cluster based design to achieve proper fit can partially be resolved by the proposed workflow using enriched SSMs.

Intra-cluster variations are often anticipated by adjustable elements, e.g. saddle height and handle bar position in bicycle design (19, 56). Enriched SSMs allows analysis of intra-cluster variations in advance, such that designers can anticipate e.g. by material characteristics, adjustability and/or increase cluster numbers to decrease intra-cluster variation.

When defining a cluster, on one hand the variation within each cluster should be minimized such that the corresponding design should cope with a minimal amount of variation, whereas at the other hand each cluster should cover an as large as possible part of the target population such that the corresponding designs fits for a maximum amount of subjects. The percentage of population not covered can be considered as a generalized percentile of the clustering, in analogy to 1D univariate anthropometric distributions.

A division e.g. along classes of equal width will generally not result in an equal amount of mass for each cluster. Product cost increases with the available number of sizes. Cluster algorithms of enriched SSMs should preferably result in an equal amount of mass in each cluster, distributing cost and gains equally along the target population, thereby minimizing intra- and maximizing inter-cluster variability. This performance can be expressed by the clustering validity index (17).

Feature-constrained shape based clustering and sizing systems. The performance of feature based, shape based and feature-constrained shape based clustering was compared in an enriched SSM of the head (46). Feature based clustering performed significantly worse than shape based and feature-constrained shape based clustering. Shape based clustering performed only slightly better than feature-constrained shape based clustering. Designers should use the latter when an enriched SSM is available, since it supports the creation of sizing tables and is intuitive to use.

Another trade-off in clustering, is the fact that the number of clusters should be minimal, to reduce costs induced by different product sizes.

Clusters can overlap. For some designs it can be useful to provide an overlap to cope with unforeseen, or inherent variations. An advantage is that overlaps in sizing systems offering alternatives for choosing the best fit available e.g. taking account of unforeseen 3D variations, but this property will be superfluous if one could ensure that a cluster clearly assures best fit for each of its members. A disadvantage is however that the assignment of a subject to its best fitting product is ambiguous and requires some trial-and-error e.g. in a retail environment.

With feature-constrained shape based clusters, no ambiguity in sizing systems remains. Moreover, as variation throughout the target population can be accurately simulated and displayed to the

designer, a good design will also anticipate any inter-cluster variation. Under that assumption, the application of the sizing system to see which product will fit for a given subject, will result in a single product that indeed fits the subject. A user-friendly sizing system that is practically and comfortable for the customer could dramatically reduce reshipment in an online retail environment.

The measurement of HL, BW, HC and AL in Figure 7 were retrieved pragmatically in a non-controlled real life context, and could be highly volatile to random and systematic errors. A concept to automatically measure HL, BW, HC and AL in the setting of a retail environment was explored in a master thesis in product development (57), see Figure 8. Such assessment methods should be investigated for (self-)sampling, robustness, accuracy, usability and comfort.

Figure 8: A concept for automatic assessment of anthropometric head features: a helmet-like device is placed on the user's head, then tuned to relevant landmarks, after which respective anthropometric features are attained geometrically and assessed by electronic aids (57).

Efficient clustering is the result of a non-straightforward trade-off comprising variation of body dimension to be coped with by the representative product, covering range, number of clusters and overall costs for different product solutions. Already established relation between anthropometric measurements and product dimensions facilitate choices for specific clusters, based on experience and former workflow. For constructing clusters based on essentially new anthropometric information and/or for essentially new products, proper tools and techniques should be developed. For example, in the presented design of the EEG headsets in three clusters, feature-constrained clustering on the fourteen electrodes points of interest, could result in even better fit (58).

CAD implementation. Enriched SSMs extend all three design strategies based on classical 1D anthropometry and preserve two important merits of designing based on 1D anthropometry: 1) the univariate character of 1D anthropometric data that can be linked to product dimensions and 2) the fact that these data represent physical parameters that can be measured relatively easy and linked with product dimensions thus giving indications for proper fit. The feature map assures that these properties are preserved effortlessly and instantaneously. Thus manikins can be parameterized and this parameterization can be used as a design basis in CAD, to transfer a design from one manikin to any other manikin. The only effort to achieve such design is setting appropriate feature values.

Given the uprising of 3D scanning, algorithms and increasing computational power, accurate and representative enriched SSMs of any body part will become available. Then, based on our observations, we recommend implementing the following workflow in a relevant CAD environment.

1. Determine the body part or region that the product should make contact with.
2. Determine which landmarks should be used as reference for a design equation and what anthropometric features should be used as sizing system and eventually also as parameters for a feature map.
3. Construct an enriched SSM of the relevant body part in step 1 that extend the landmarks and features from step 2. All other features can be discarded, the enriched SSM will only take account the variation that is relevant to the specific design.
4. Construct the feature map as a basis for feature-constrained shape based clustering.
5. Determine cluster characteristics:
 - a. maximum allowable error with relation to fit,
 - b. preferred maximum number of clusters
 - c. minimal allowable percentage covered by the clustering
6. Construct clusters and representative manikins for each cluster (mean or medoid), satisfying properties a., b. and c. in step 4. Note these may be conflicting condition so a trade off prior to cluster construction might be appropriate. Display dense geometric information on the representative manikins.
7. Design on a representative manikin to cope with maximal variation. Feature mapping can be used to transfer the same design to any other representative manikins, however persistently coping with variation through the respective cluster.
8. Design a practical sizing system that takes an end user's feature in step 2, thus assigning the best fitting product to that end user.

5.3 Potential for individual fit

A CAD/CAM platform for design for individual fit can be implemented similarly. The first three steps are as in the workflow for design for fit within clusters. Then one could proceed in the following way.

1. Determine the body part or region that the product should make contact with.
2. Determine which landmarks should be used as reference for a design equation and what anthropometric features should be used as sizing system and eventually also as parameters for a feature map.
3. Construct an enriched SSM of the relevant body part in step 1 that extend the landmarks and features from step 2. All other features can be discarded, the enriched SSM will only take

account the variation that is relevant to the specific design.

4. Construct the feature map to generate individual models.
5. Analyse eventual errors induced by the feature map.
6. Construct a design equation on features and landmarks closely fitting the body surface generated by the feature map coping with eventual errors.
7. Design a practical sizing system that takes an end user's feature in step 2
8. Connect the parameterized design to a platform for personalized production, to be tuned by a subject's individual features.

Mass customization can be achieved by a combination of design for universal- or fit within clusters with a design for individual fit, where some parts are predefined (e.g. chain, gears, handles) and others (e.g. frames) can be tuned to the user's individual dimensions (56). In the light of this, enriched SSMs have the potential for efficient design for mass customization.

6. Conclusion

Statistical shape models have the ability to take account of the full variation of the human body. We have introduced the concept of enriched statistical shape models. This data structure extends classical 1D anthropometric values and their statistical distributions. Three workflows are proposed to deploy enriched statistical shape models for the design wearable products: design for universal fit, design for fit within clusters including product-specific sizing systems and design for individual fit. These methods extend the workflow of traditional ergonomic design based on 1D anthropometric data. All methods rely on the feature map that comes with an enriched statistical shape models: the best approximating shape can generated from any set of feature values. An eventually induced error can be controlled by design or by incorporating more features, if available.

A proof of concept was given for EEG headsets with an enriched statistical shape model of the human head. EEG headsets are a good study example because they require a close fit on the human head. The human head is adequate described by an enriched statistical shape model because is of static nature and has a complex geometry. The presented cases show that our proposed methods can be implemented in practice and that enriched statistical shape models can be used to construct design equations that can be tuned by classical anthropometric features. Our cases exhibit a merit in current industrial design related to fit and comfort. They also indicate that features can be obtained in a real life setting to tune the body form and related design equation. For design for universal fit, merits were already verified by experiments and inductive statistics. For design for sizing systems and design for individual fit, more experiments are needed to prove the observed added value.

The potential for design for individual fit is most striking since it incorporates the ability of mass-customization and individual designs. For efficient deployment however proper CAD tools and techniques are required. With the uprising of mass customization and personalized production techniques, the potential of enriched statistical shape models complemented with proper tools and techniques, might be driving the development and manufacturing of new wearable products.

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