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Thermal Profiling: Can Individuals be Grouped into Thermal Families?

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ABSTRACT

Many apparel companies are currently faced with the demands of a mature marketplace while trying to satisfy customers who expect apparel that is highly customized. However, making a customized garment for each customer is typically not feasible. Thermal profiling solves this problem for thermal regulatory apparel by grouping consumers into specific thermal families. These thermal families define micro-consumer groups for which mass-customized functional apparel can be created. This study identified whether individuals can be grouped into thermal families, then examined which demographic and anthropometric variables were most associated with thermal profiling. Data mining procedures were used to extract individuals from a pre-existing database with a total sample size of 796. First, utilizing a hierarchical cluster analysis, each individual, by gender, was placed into one of three thermal families (uniform, v-shaped, and abdominal trough). These families were determined by clusters of spatial temperature distributions. Next, ten separate statistical goodness-of-fit measurements were employed to determine the "fit" of the individual to their assigned thermal family. Lastly, the thermal families were correlated with selected demographic and anthropometric variables. Results indicated that there were at least three distinct thermal families, and that individuals could be categorized by thermal profile. Neither age nor exercise frequency was correlated with a thermal pattern and therefore could not be used as a means of categorizing individuals into thermal families. In contrast, results indicated that several anthropometric measures could be used as a proxy to predict an individual's thermal family. In summary, for apparel companies seeking to gain a competitive edge, thermal profiling and the resultant thermal families may be a tactical advantage in a mature, competitive market.

Keywords: Thermal imagining, thermal profiling, 3D mapping, data mining

Introduction

Today, apparel companies who are engaged in the design, production, and sale of functional apparel are finding themselves in an increasingly mature, competitive marketplace. Simultaneously, consumers have expressed the desire for apparel that is customized to their bodies as well as to their intended end use. More recently, with the advent of new technologies, apparel mass-customization has become a means of increasing sales by creating and developing specific products for multiple, well-defined, micro-consumer groups. These highly customized products provide value to the consumer and offer growth opportunities and strategies for mature markets like the sports apparel industry (Parrish, Cassill, & Oxenham, 2006). In an attempt to grow sales and expand markets, some functional apparel producers have begun to develop high value products where innovation and customization are more important than price to this consumer group (Ramachandran & Kanakaraj, 2012). As most functional apparel is still designed without consideration of individual differences in thermal regulation, for functional apparel companies seeking to gain a competitive edge, recognition of the thermal differences between individuals may be a strategic opportunity. However, making a customized functional garment for each customer is typically not feasible. Shani and Chalasani (1992) recommend that companies first look at the needs of a few individual customers, then to achieve cost efficiencies aggregate on the basis of similarities. Thermal profiling solves this problem by grouping consumers into specific thermal families, creating micro-consumer groups which can then be targeted by designers and product developers to create garments with heat retention or releasing zones of specific sizes and locations while still maintaining cost efficiencies. This study's intent was to identify whether individuals could be grouped into thermal families, then examined what attributes and anthropometric variables were most associated with thermal profiling.

Background and Justification

Thermal Profiling

Thermal profiling involves grouping individuals according to similar heat patterns and other attributes such as body shape. Previous research linking somatotype to skin temperature focused on an individual's amount and location of fatty tissue and skin surface area and then later, the role of muscle in thermoregulation in a variety of environments (Anderson, 1999). Anderson (1999) found that individuals differing in somatotype appeared to respond differently to variations in both ambient and core temperatures, but the interrelations were complex. A study of military men and women found that individuals, classified into five major somatotype groups, responded to heat stress differently based on their somatotype (Yokota & Bathalon, 2008). Savastano et al., (2009) found that obese adults displayed different thermal patterns on the belly region than their thinner counterparts. Author (2011) explored thermal profiling in a study using women, 18-25 years of age with variable BMIs. Results from this study indicated that individuals could be grouped according to a thermal profile and that those with normal BMI showed less thermal variability than individuals classified as overweight or obese. In summary, although the link between somatotype and skin temperature is still cloudy, there do appear to be thermal patterns based at least in part on somatotype. It is expected that there is a discrete set of categories where the thermal profiles of all the subjects in each group correlate highly, but where variations exist between categories.

When creating classifications of thermal families the needs of apparel designers, manufacturers, and retailers must be taken into account. Thus, although a greater number of thermal families provide more choices and closer fit into a family for the consumer, it can overwhelm the designer with information. Additionally a large number of thermal families can cause problems and increased costs with production for the manufacturer and inventory difficulties for the retailer. Therefore, it would be most helpful to develop the fewest number of thermal families that fit the greatest number of consumers. The application of data mining techniques can be used to cluster the data into thermal families.

Data Mining

Data mining techniques first began in the 1950s as an outcome of artificial intelligence and machine learning. For the next decade, academicians continued to develop algorithms and in the 1960's the term data mining was coined, but had derogatory connotations to describe the practice of randomly wading through data looking for significant patterns (Fayyad, Piatetsky-Shapiro, Smyth, 1996). Also during this time, clustering techniques and similarity measures were developed by scholars in the information retrieval field (Ayre, 2006).

Through the 70s and the 80s the field of data mining continued to evolve and mature. This growth was assisted by the expansion of microprocessors as well as the development of new programming languages and computing techniques (Ayre, 2006; Collier, Carey, Grusy, Marjaniemi, & Sautter, 1998; Dunham 2003). Eventually, the field evolved into three areas: advanced database systems, data warehousing and data mining, and web-based databases (Han & Kamber, 2006).

By the beginning of the 1990s, the term Knowledge Discovery in Databases (KDD) had been coined and data mining was recognized as a core element of KDD (Collier et al., 1998, Fayyad Djorgovski, & Weir, 1996). This decade saw the emergence of data mining as an industry and as a valuable tool to businesses. Companies, which had been keeping records of customer transactions, reached the conclusion that their records were valuable and moved to apply data mining to their historical data or data warehouse (Collier et al, 1998). With the advent of sophisticated query techniques, data mining expanded beyond business applications and began to be used in scientific inquiries (Keating, 2008).

Today, data mining has become mainstream with easier to use algorithms and statistical packages. Data mining has been adopted by a wide variety of industries and organizations including but not limited to medical and financial industries, e-tailing companies and state and federal governments for a variety of uses (Adomavicius & Bockstedt, 2008; Apte, Liu, Pednault & Smyth 2002; Fayyad et al., 1996; Hormozi & Giles, 2004; Kohavi, Mason, Parekh, & Zheng, 2004). Other applications include health risk predictions, production scheduling and classification of biological sequencing (Chae, Ho, Cho, Lee, & Ji, 2001; Maddouri & Elloumi, 2002; Sha & Liu, 2005). More recently, with the increase in large multidimensional databases containing images, text, and uncertain information, the development of data mining techniques to search for objects with similar shapes, print and image patterns or uncertain data has become critical (Adomavicius & Bockstedt, 2008; Aggarwal & Yu, 2009; Carlin, 2001; Frentzos, Gratsias, Theodoridis, 2009).

Data Mining in Apparel

As with other industries, the textile/apparel industry has embraced data mining as a means to gain a competitive advantage, facilitate and increase sales, and to recognize efficiencies in design and production.

Retail industry. The apparel retail industry in its various formats (brick and mortar, e-tailing, catalog, etc) has realized the competitive advantage of utilizing data mining techniques. Regardless of a retailer's format, data mining is an essential tool for consumer relationship management (CRM). CRM is a long-term business approach to building relationships between the business and the consumer, maximizing value to each (Chen, Sain, & Guo, 2012; Ngai, 2005; Ngai, Xiu, & Chau, 2009). Strategic decision-making is strengthened when retailers employ data mining techniques to analyze and cluster consumers by past product purchasing patterns, shopping behavior and frequency, and brand loyalty for improving customer acquisition and retention (Hormozi & Giles, 2004; Mukherji, 2012). These same techniques can also be used to create a model for predictive profiling, which predicts future consumer purchasing behavior based on historical data (Apte et al., 2002). Today, e-tailing activities generate tremendous amounts of data, creating an even greater need for data mining systems. This includes sales trend analysis, creation of customer product rating systems, and cross and custom-bundling products or services for individual customers (Grenci & Watts, 2007). Data mining can identify customer navigation patterns and personalize the online experience for the consumer with the intent to reduce choice, resulting in a greater likelihood of a purchase. Data mining can also be used to analyze abandoned shopping carts and evaluate online marketing events (Kohavi et al., 2004; Zhang, Edwards, & Harding, 2007).

Anthropometrics & Sizing Systems. Utilization of data mining techniques to classify body shapes from anthropometric data to create standardized sizing systems first appeared in the past decade. Hsu and Wang (2005a,b) employed a decision tree technique to mine data in an effort to classify the body shapes of Taiwanese soldiers in order to establish a standardized sizing system. The decision tree technique allows the user to categorize data using rules, resulting in a tree-shaped hierarchy with rules defining the branches of the tree. Four body groups emerged along with the creation a sizing system that had the highest coverage rates for the fewest groups. This work was extended to the development of garment-size charts for adult females in Taiwan using a cluster-based data mining approach (Hsu, Lin, & Wang, 2007). Cluster analysis is one of the most important data mining techniques used to solve classification problems; clustering techniques are used to categorize data so that intragroup variances are minimized while intergroup variances are maximized (Dunham, 2003). Resultant data mining activities revealed three body types classified by girth and height sizing variables, with the revised size charts covering 95.8% of the adult Taiwanese females.

Most recently, Hsu, Lee and Kuo (2009) have applied data mining techniques to the classification of body shape for the adult female Taiwanese ready-to-wear (RTW) domestic and export markets. The anthropometric database consisted of 89 female subjects; eleven relevant anthropometric variables were determined most suitable for creating size charts, and a fuzzy clustering-based data mining procedure was utilized (Hsu et al., 2009). Fuzzy clustering techniques are similar to deterministic clustering techniques, although in fuzzy clustering data elements can belong to multiple clusters as opposed to just one cluster; a membership level is maintained for the data/cluster pair, indicating the strength of association of the data element with the particular cluster. As in earlier work, new classified body types were identified and new sizing systems developed for garment manufacturers. Other researchers used similar data mining techniques to establish sizing systems for elementary and high school students (Chung, Lin, & Wang, 2007); to classify individuals by body shape and then to identify measurements that are of most importance for fit for the Dutch population (Pena, Viktor, & Paquet, 2009); and to produce a new suit sizing system for men (Esfandarani & Shahrabi, 2012).

Methodology

Data mining includes a sequence of steps: defining the objective, data preparation, and evaluating and applying the results. This section describes the methodology used in this study to determine whether individuals could be categorized into specific thermal families based on demographic and anthropometric information for the purpose of mass-customizing functional apparel. This study is limited in scope to the torso region.

Defining the Objectives

The intent of this study was to explore and analyze a pre-existing database of human anthropometric measurements and thermal images of the human torso to determine whether participants could be used to categorize into thermal families. This study also examined whether anthropometric data could be used as a proxy to thermography for categorizing individuals into thermal families. To achieve this objective the following questions were proposed:

1. Can individuals be grouped into thermal families?
2. Do demographic variables (age and activity level) correlate with thermal families?
3. Do anthropometric variables (height, weight, body max index (BMI), neck to hip height, bust/chest girth, belly girth, waist girth and buttock girth) correlate with thermal families?
4. Can any of these measures be used as a proxy to thermography to predict which thermal family an individual might fit in?

The answers to these questions were defined as the objectives of this study. Most importantly, a positive response to question four would validate the use of these variables as a proxy for thermal imaging. This then would allow for mass-customize functional apparel targeted towards specific subgroups, without the need for thermal images to be taken for each individual.

Data Collection and Preparation

Data used in this study came from a pre-existing relational database consisting of human subject data from a rural, upper Midwestern college town in the United States. The database contained over 881 individuals, comprising both male and female subjects, from 11 to 92 years old with diverse somatotypes. The median age for females was 22 years old, while the median age for males was 21 years old. Data collection was initiated after Institution Review Board (IRB) approval was obtained. Subjects were recruited using a variety of methods as appropriate for the age category. Recruitment methods included the local public school system, summer camps, on-campus email and online university announcement systems, presentations at local professional and service organizations, newspaper and radio, flyers throughout the local community, and word of mouth. Subject recruitment was an on-going activity with new subjects added to the database on a weekly basis (Author, 2011).

Subject data was collected using a 3D body scanner, a thermal camera, a stadiometer, and a standard demographic questionnaire. The resulting non-personalizable database contained extensive records for each individual including 120 anthropometric measurements, BMI, weight, basic demographic data, thermal images of the torso, and 3D body scans for a total of approximately 65 gigabytes of data. Cleaning the data was addressed prior to mining the database. The database was checked for missing or invalid data, removing all the participants with missing data. As a result, of the 881 individuals in the data base, 85 participants were deleted from the set, leaving a total sample size of 796 participants used in data mining procedures.

Data Analysis and Evaluation

Grouping the greatest number of people into the fewest number of thermal families results in a loss of granularity, but achieves a simplification most useful to apparel designers. These groupings were accomplished through data mining utilizing a hierarchical cluster analysis. This is one of the most important data mining techniques as it provides a means of data reduction and of solving classification problems (Hsu et al., 2007). For each gender, three thermal families (uniform, v-shaped, and abdominal trough), were determined by clusters of spatial temperature distributions, and were specified based on the criteria to keep the number of families small and by the results of data mining activities on the thermal images (see Figure 1).

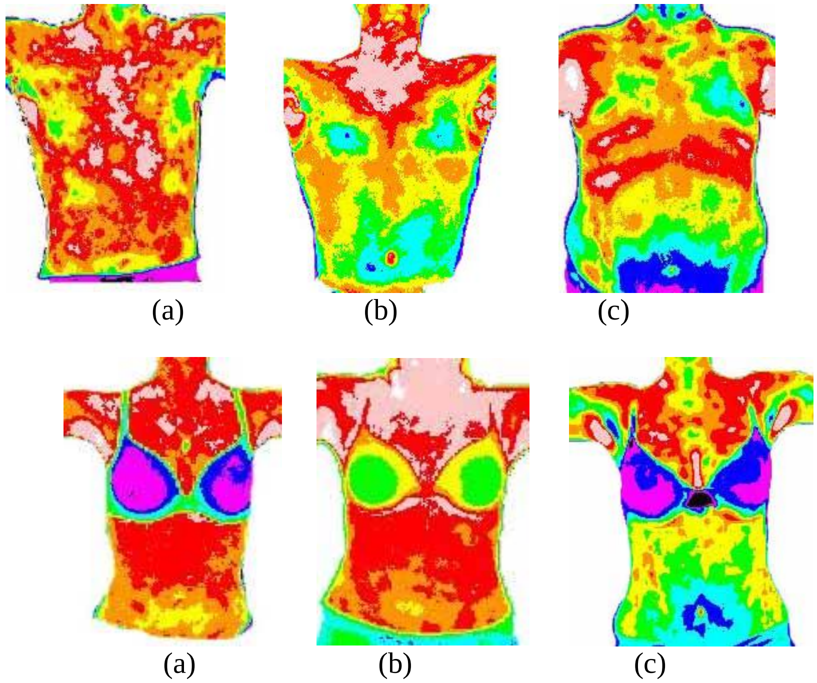

Figure 1. Sample male and female thermal families: (a) uniform, (b) v-shaped, and (c) abdominal trough

First, a representative male and female thermal image was loaded into MATLAB as a reference image. Next, each thermal image from the population sample was loaded into MATLAB iteratively in a loop. For each image, image registration was performed to the reference image, so that thermal profiles for each subject were mapped onto the gender appropriate reference image (Author, 2011). This step is important as it ensures that all the images are the same size allowing for pixel based image comparisons. After all the images were registered, pixel-based statistics were computed to determine descriptive statistics for each zone. The univariate statistics calculated were computed using the pixel temperature values within the four regions (neck, lower left oblique, lower right oblique and lower abdominal) as shown in Figure 2. The minimum, maximum, range, mean and standard deviation statistics were computed and compared to the model's intrazonal statistics for the three thermal patterns. These zonal statistical measures were also compared across zones and compared to the model's interzonal statistics for each of the six zone combinations. This led to ten separate statistical goodness-of-fit measurements, which provided the basis for the distance metrics used in clustering the individuals. An excellent fit meant that the subject fit the selected thermal pattern model in all 10 statistical measures, a good fit meant that the subject statistically fit the assigned model best in at least 7 of the statistical measures, and a fair fit meant the subject fit best in the assigned model in fewer than 7 statistical measures, but better than the other patterns.

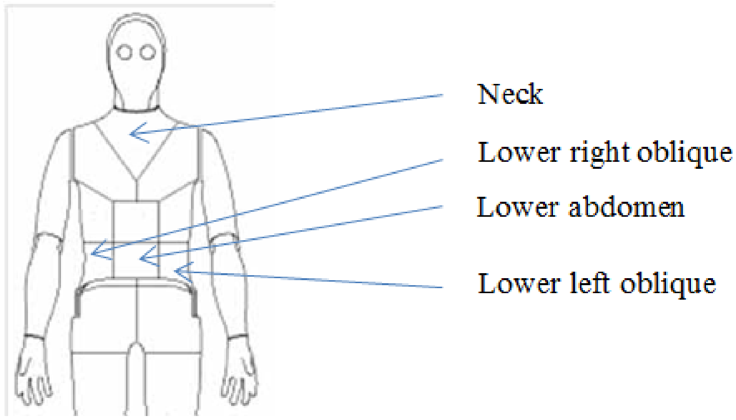

Figure 2. Zonal regions selected for cluster analysis

Once the goodness-of-fit for the thermal patterns was completed and all the participants were clustered into one of the three thermal families, the thermal patterns were then correlated with demographic and anthropometric attributes. Although the body scanner captured over 120 different measurements for each participant, not all of the anthropometric variables were suitable for use in correlation analyses, and so were removed from the variable set. Examples of measurement variables that were removed included scapula height, breast height, neck diameter, upper torso torsion and many others. The authors limited the variable set for convenience in statistics and also to select variables that could be used in a customer e-commerce environment, where customers could use a convenient proxy measure for thermal family selection. Therefore, in coordination with the judgement of domain experts, this study identified the following anthropometric measurement variables: height, weight, BMI, bust/chest girth, belly girth, waist girth, and buttock girth. Demographic variables included age and exercise frequency.

Pearson correlation coefficients were calculated for each combination of measurement variables aforementioned along with thermal pattern results. If a correlation were found to exist between the thermal pattern and any measurement variable, it may serve as a proxy to determine an appropriate thermal family in the absence of a thermal camera.

Lastly, ANOVA analyses were performed on several of the correlated variables to determine whether the means of each thermal pattern for the various anthropometric measurements were statistically different or not.

Results

Table 1 summarizes the means, the 95% confidence intervals for the means, the range of values and the median for the study. As shown in Table 1, over two-thirds of the total sample was female. Among each anthropometric measurement, there existed a diverse range of values between individuals. These participants were predominantly from the north-central region of the United States, with the majority college-aged students. Table 1 shows a wide range of BMI for both males and females; however, the majority of participants were borderline overweight. Additionally, the means were significantly different between genders for the majority of the anthropometric measurements with the exception of belly girth and buttock girth. It should be noted that the 95% confidence intervals are small compared to the range, showing that the data is highly skewed with small standard deviations and large sample sizes (attributes used to determine the 95% confidence intervals for the mean). This is due to the fact that most of the subjects in our database are college students.

Table 1. Summary of Anthropometric Statistics for Males and Females (95% confidence intervals)

Category	Female			Male		
	Mean	Range	Median	Mean	Range	Median
Sample Size	541			255		
Age (yr)	31.89 (±1.47)	11-87	22	24.44 (±1.34)	12-71	21
Height (cm)	165.05 (±0.57)	142.24-187.96	165.10	177.51 (±0.96)	147.57-195.50	177.80
Weight (kg)	66.03 (±1.20)	34.56-127.01	63.50	80.41 (±1.88)	39.01-147.87	78.38
BMI (kg/m^2)	24.24 (±0.43)	13.38-44.85	23.08	25.46 (±0.53)	19.44-30.01	24.75
Bust/Chest Girth (cm)	95.96 (±0.93)	67.49-136.96	94.03	102.74 (±1.42)	70.05-156.03	101.77
Belly Girth (cm)	87.30 (±1.03)	59.39-131.04	85.22	89.09 (±1.50)	63.17-153.90	86.33
Waist Girth (cm)	79.71 (±1.14)	54.64-136.78	76.45	85.82 (±1.43)	61.19-142.98	83.21
Buttock Girth (cm)	101.89 (±0.95)	72.44-150.60	99.82	101.46 (±1.08)	79.15-153.59	100.33

Table 2 summarizes the frequencies stratified by gender as categorized first by BMI, then by thermal pattern. As presented below, the majority of both males and females were classified by BMI as normal to overweight. The predominant thermal pattern demonstrated by both males and females was V-shaped, 60.1% and 70.6% respectively, followed by abdominal trough with 20.7% of the sample for both sexes.

Table 2. Frequency of Males and Females Categorized By BMI and By Thermal Pattern

Gender	Total	BMI				Thermal Pattern		
		Underweight	Normal	Overweight	Obese	Uniform	V-shaped	Abdominal Trough
Female	541	30	332	111	68	47	382	112
Male	255	3	129	84	39	48	154	53

Note: BMI category: underweight (< 18.5); normal (18.5-25.0); overweight (25.0-30.0); obese (>30.0).

For each of the participants categorized in Table 2, the fit of each individual to the assigned thermal pattern was computed; these results are shown in Table 3. The fit was categorized as excellent, good or fair based on pixel-based statistics of temperatures. For both males and females, the majority of the participants were an excellent or good fit to the assigned model. However, roughly a third of females and a quarter of males were only fair fits.

Table 3. Fit of Participants to Thermal Patterns

Thermal Pattern	Female			Male		
	Excellent	Good	Fair	Excellent	Good	Fair
Uniform	13 (28%)	19 (40%)	15 (32%)	11 (23%)	23 (48%)	14 (29%)
V-shaped	67 (18%)	179 (47%)	136 (36%)	48 (31%)	62 (40%)	44 (29%)
Abdominal Trough	31 (28%)	45 (40%)	36 (32%)	28 (53%)	16 (30%)	9 (17%)

Table 4. Correlation Coefficients Between the Different Attributes Examined Among Females

	Age	Height	Weight	Exercise	BMI	Girth				Thermal
						Bust	Belly	Waist	Buttock	Pattern
Age	1									
Height	-0.13	1								
Weight	0.32	0.28	1							
Exercise[1]	0.10	-0.03	-0.01	1						
BMI	0.39	-0.10	0.93	0.00	1					
Bust Girth	0.41	0.40	0.88	-0.02	0.90	1				
Belly Girth	0.45	0.10	0.92	-0.02	0.92	0.91	1			
Waist Girth	0.53	-0.00	0.89	0.01	0.93	0.92	0.96	1		
Buttock Girth	0.42	0.16	0.93	-0.01	0.90	0.84	0.91	0.88	1	
Thermal Pattern	0.37	-0.11	0.75	0.00	0.82	0.76	0.76	0.77	0.74	1

[1] Self-reported exercise frequency scale: 0 times per week, 1-2 times per week, 3-4 times per week, more than 4 times per week.

Tables 4 and 5 summarize the bivariate Pearson correlation coefficients for females and males between the self-reported exercise frequency, BMI, the primary anthropometric measurements, and the categorized thermal patterns. As shown in these tables, among the population studied there was no statistical correlation between the self-reported exercise frequency and the anthropometric measures. Likewise, no statistical correlation existed between exercise or age and the associated thermal pattern. However, the thermal pattern correlated well with all the anthropometric measures.

Table 5. Correlation Coefficients Between the Different Attributes Examined Among Males

	Age	Height	Weight	Exercise	BMI	Girth				Thermal
						Chest	Belly	Waist	Buttock	Pattern
Age	1									
Height	-0.10	1								
Weight	0.18	0.46	1							
Exercise[1]	0.04	0.00	0.01	1						
BMI	0.27	0.01	0.89	0.01	1					
Chest Girth	0.31	0.25	0.88	0.03	0.87	1				
Belly Girth	0.34	0.19	0.87	-0.11	0.89	0.86	1			
Waist Girth	0.41	0.17	0.88	-0.08	0.91	0.89	0.97	1		
Buttock Girth	0.13	0.30	0.87	-0.04	0.82	0.79	0.86	0.82	1	

Thermal Pattern	0.29	0.03	0.77	0.03	0.86	0.76	0.76	0.78	0.67	1

[1] Self-reported exercise frequency scale: 0 times per week, 1-2 times per week, 3-4 times per week, more than 4 times per week.

Table 6. ANOVA Showing the Statistical Differences in Means of Selected Anthropometric Measurements for the Different Thermal Patterns.[1]

	Experimental Group Means (95% confidence intervals)				
Measurement	Uniform	V-shaped	Abdominal Trough	F	η^2
Females					
BMI (kg/m^2)	17.95 (±0.90)	22.92 (±0.61)	31.38 (±2.64)	392.49	0.59
Waist Girth (cm)	65.20 (±1.19)	75.52 (±0.72)	100.03 (±2.21)	473.35	0.64
Belly Girth (cm)	72.70 (±1.37)	83.95 (±0.72)	104.84 (±1.87)	416.77	0.61
Bust Girth (cm)	83.86 (±1.59)	92.76 (±0.63)	112.21 (±1.74)	422.42	0.61
Males					
BMI (kg/m^2)	20.39 (±0.88)	24.76 (±0.76)	32.09 (±2.16)	416.64	0.77
Waist Girth (cm)	74.31 (±1.42)	83.62 (±0.88)	102.61 (±3.01)	231.11	0.65
Belly Girth (cm)	77.46 (±1.57)	86.78 (±0.98)	106.36 (±3.26)	201.96	0.62
Chest Girth (cm)	90.34 (±1.84)	101.48 (±1.13)	117.70 (±2.54)	175.74	0.58

[1] $\alpha=0.05$, $F_{crit}=3.01$ for females and 3.03 for males

Table 6 displays the results of ANOVA analyses, grouped by gender and by thermal family, for BMI, waist girth, belly girth and bust/chest girth. As shown in Table 6, the means of the measurement variables for each thermal family were significantly different from each other. These results indicated that there was a strong correlation between these anthropometric measurements and the spatial distribution of thermal transfer in the human torso. It should be noted that the 95% confidence intervals are small compared to the range, showing that the data is highly skewed with small standard deviations and large sample sizes (attributes used to determine the 95% confidence intervals for the mean). This is due to the fact that most of the subjects in our database are college students.

Table 7 presents the proposed cutoff values for the selected anthropometric measurements used as proxies for thermography when categorizing individuals into thermal families. These cutoffs are useful for the population in this database, but most likely not for the population in general. Further studies on other population groups will be needed before generalizations to the entire population or regional population can be made. These cutoff ranges were determined based on the distribution of data for each measurement variable, with overlap between distributions.

Table 7. Proposed cutoff values to for various proxy measurements

Measurement	Uniform	V-shaped	Abdominal Trough
Females			
BMI (kg/m^2)	<19	19-27	>27
Waist Girth (cm)	<68	68-81	>81
Belly Girth (cm)	<76	76-92	>92
Bust Girth (cm)	<89	89-104	>104
Males			
BMI (kg/m^2)	<22	22-29	>29
Waist Girth (cm)	<79	79-92	>92
Belly Girth (cm)	<81	81-97	>97
Chest Girth (cm)	<94	94-109	>109

Conclusions

The premise of this study starts with the question “Can individuals be grouped into thermal families?”. Additional questions were then posed to determine if any demographic or anthropometric variables could be correlated with thermal families. Lastly, the authors asked whether these variables could serve as a proxy for thermal images and categorizing individuals into thermal families.

Can individuals be grouped into thermal families? The results of this study provide an affirmative response to this question. This study determined that both males and females could be categorized into at least three distinct thermal families, each with a unique thermal pattern. By far the most common, the v-shaped thermal pattern contained the majority of individuals for both sexes. This thermal family was represented by a v-shaped heat pattern beginning at the neck and ending mid-sternum, with the rest of torso region at a lower temperature. The abdominal trough family was the second most populated group. This family was characterized by a significantly cooler region in the belly area than the rest of the torso region. Individuals who were placed into this thermal family were typically overweight and obese. The authors speculate that excess abdominal belly fat acted as an insulating factor, causing this particular pattern. The uniform thermal family comprised the smallest group. This thermal family was characterized by an overall, consistent, relatively warm torso. Individuals in this group tended to be either underweight or on the low end of a normal BMI. The lack of cooler skin temperatures among this group is notable. It is likely that the lack of body fat results in skin temperatures not significantly different than the core body temperature. Further analysis provided additional support for the three thermal families; the majority of participants were an excellent or good fit to the assigned family. However, roughly a third of females and a quarter of males were only fair fits, indicating that changing the data mining parameters may result in a fourth thermal family.

Do demographic variables correlate with thermal families? This study indicated that neither age nor exercise frequency was correlated with thermal patterns and therefore could not be used as a means of categorizing individuals into thermal families. This result should be viewed with caution as the majority of participants in the population sample were young adults with significantly fewer older or elderly adults. Additional thermal profile research needs to be conducted using an older adult population sample to determine if age is or is not a predictor variable. Likewise, exercise frequency was self-reported and there were no detailed follow-up questions such as level of exercise intensity or the type or average duration of exercise. Research comparing low/moderate exercise with high/athletic exercise to determine if physical activity is correlated with thermal families would be of significant use to the sporting and athletic wear industries.

Do anthropometric variables correlate with thermal families? The results indicated that there existed a strong correlation between the anthropometric measurements examined and the spatial distribution of thermal transfer in the human torso. Therefore, anthropometric measurements could be used to determine an individual’s likely placement within a particular thermal family.

Can any of these measures be used as a proxy to thermography to predict which thermal family an individual might fit in? This study showed that several of the anthropometric measures could be used as a proxy to predict the consumer’s thermal family. BMI provided the best proxy according to this study, but among readily available measures weight and waist girth also provided convenient measures which the consumer may know. The belly and bust/chest girths may also be used as a proxy to thermal imaging, but these measurements may not be known by the consumer so are not convenient proxy measures. Also, for the belly and bust/chest girths, the cutoffs for differentiating between the thermal patterns and the measurement were not as well defined; there was much more overlap in the range of values for these measurements than for BMI, weight or waist girth.

Industry Applications

As thermal imaging each potential customer is impractical, the identification of proxy measures is important for companies who are interested in developing garments that better meet their customers' thermal comfort needs. It is important that the proxy measures are typically known by consumers, providing the means for customer self-selection of the appropriate garment. Additionally, any proxy measures must also provide a means of segmenting a larger consumer base into micro consumer groups.

The customers' ability to self-select a thermal family may be beneficial to apparel companies who are pursuing mass customization strategies. Companies engaged in mass customization production should ultimately produce items that best meet their customers' needs, including thermal comfort. Building upon a self-selected thermal profile, a company could cater to their consumers' preference for uniqueness by also allowing for the selection of color, style, and fabric choices.

For sport and athletic companies seeking to gain a competitive edge, thermal profiling and the resultant thermal families may be a tactical advantage in a mature, competitive marketplace. Marketing literature substantiates that the success of a niche marketing strategy is often product differentiation through factors such as innovation, technology, and customization (Parrish et al., 2006). Responding to the needs of customers is also an important aspect of a niche marketing approach. The thermal images showing zonal heat patterns can be useful to apparel designers and product developers to create mass-customized functional apparel. This apparel may contain heat retention or releasing zones of specific sizes and locations for each micro-consumer group. Ultimately, consumers today want and expect more variety in product offerings that meet their specific needs; the one size fits all is no longer acceptable. Utilization of thermal families to guide garment design is one resource that fulfills the customer's need for differentiation and product personalization.

Limitations

During this data mining study, several limitations were discovered which made the data mining and analysis difficult. These limitations existed primarily because the research protocol was not initially designed with thermal imaging data mining activities in mind, but was focused on 3D body scanning. The most troublesome issue for female participants came from the diverse sizes and types of bras worn. The initial flyers and brochures specified that females must wear tight-fitting bras, but did not specify bra type. Females wore bras of varying sizes, and in several cases the bras covered a majority of the torso region, making it difficult to register the images and categorize the individuals. A second, related limitation involved the underwear and the belly button. The belly button was used as a landmark for image registration purposes, but in several cases individuals (both males and females) wore high-riding underwear which covered the belly button. This affected the temperature statistics for the lower abdominal and oblique regions as well as made it difficult for registration. Lastly, the exercise frequency obtained for each individual was self-reported, and each individual's idea of what constituted exercise were different. This, as well as the lack of statistical correlation, leads the authors to conclude that additional research is needed to determine the efficacy of a self-reported exercise frequency and intensity questionnaire as a proxy for thermal imaging. This study also has limitations in the demographic distribution of the study participants. Almost all of the participants came from the north central region of the United States, and many of them were college students. Due to the lack of participants from other geographic regions or age groups, statistical analyses could not be done to determine whether these factors contributed to the thermal distributions.

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