Delft University of Technology

Design smart clothing using digital human models

Scataglini, Sofia; Danckaers, Femke ; Huysmans, Toon; Sijbers, Jan; Andreoni, Giuseppe

DOI
10.1016/B978-0-12-816713-7.00053-2

Publication date
2019

Document Version
Final published version

Published in
DHM and Posturography

Citation (APA)
Scataglini, S., Danckaers, F., Huysmans, T., Sijbers, J., & Andreoni, G. (2019). Design smart clothing using digital human models. In S. Scataglini, & G. Paul (Eds.), *DHM and Posturography* (pp. 683-698). Academic Press. https://doi.org/10.1016/B978-0-12-816713-7.00053-2

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

Chapter 53

Design smart clothing using digital human models

Sofia Scataglini[1], Femke Danckaers[2], Toon Huysmans[2,3], Jan Sijbers[2] and Giuseppe Andreoni[4,5]

[1]Department of Product Development, Faculty of Design Sciences, University of Antwerp, Antwerp, Belgium; [2]imec – Vision Lab, Department of Physics, University of Antwerp, Antwerp, Belgium; [3]Applied Ergonomics and Design, Department of Industrial Design, CE Delft, The Netherlands; [4]Politecnico di Milano – Design Dept, Laboratory TeDH - Technology and Design for Healthcare, Milan, Italy; [5]IBFM - CNR, Consiglio Nazionale delle Ricerche - Istituto di Bioimmagini e Fisiologia Molecolare, Milan, Italy

1. Introduction

Smart clothing or "intelligent textile" represents the new class of wearable technology, the 2.0 era of interactive technologies, intended to be attractive, comfortable, and "fit for purpose" for the identified user (Scataglini, Andreoni, & Gallant, 2019a, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019b, Scataglini, Danckaers, Haelterman, Huysmans, Sijbers and Andreoni, 2019c).

The fusion of the two borders, the electronics and the textile, opens up new fields to be investigated in applied ergonomics and human factor field. Fibers and filament yarns, together with woven and nonwoven structures that feature electronics, capable of sensing passively and actively, activate and interact in response to the environmental and the wearer's conditions. In addition, they adapt their behavior to the given circumstances becoming very smart (Choo 2009; Stoppa & Chiolerio, 2014). The textile sensors can detect bioelectric (electrocardiography [ECG], EMG, EEG, EOG, ENG), thermal (temperature and the relative surface map), mechanical (movement, contact pressure), optical, and chemical signals (sweat composition, inhaled/exhaled air composition, contaminants). They can include active functionalities such as power generation or storage, assistive technologies, human interface elements, and radio frequency categories. The innovative fusion gave us the idea that they only appeared recently to the audience, but actually, the history of smart textile goes back over 75 years. Images from a patent of 1942 show concepts developed around electronics in clothing, developed by Cover (1942). They show a two-way radio garment or coat and equipment for transmitting and receiving audible signals for use by policemen, sailors, miners, or others working in tunnels or underground (Fig. 53.1).

Projects continued for over 50 years on a smaller scale and across many research labs and private organizations, but commercial progress was minimal for decades. As of 2000s, the idea came up more concrete in the military field with the development of the Georgia Tech Wearable Motherboard or Smart Shirt, which gave rise to the interactive textile and indeed the fusion of the two boarders (Park & Jayaraman, 2003). The Smart Shirt provided an extremely versatile framework for the incorporation of sensing, monitoring, and information processing devices. It featured a single plastic optical fiber spirally integrated into the fabric with a novel weaving process to eliminate discontinuities at the armholes or seams to detect bullet wounds. It is the first smart shirt addressed to monitoring vital signs on soldiers such as heart rate, respiration rate, electrocardiogram, body temperature, and pulse oximetry in an ecological and nonintrusive way.

Sensing clothing offers the unique opportunity to implement a real not intrusive monitoring, i.e., it represents an extraordinary tool for observing and analyzing the complex human-machine-environment system in specific tasks (Scataglini et al. 2017).

In this context, the design research is passing through scholarly boarders between semantic, syntactic, and pragmatic dimension of the research (Mattila, 2006). The semantic part can be defined by the context of the end user identifying the environment. Then the syntactic component takes care of the design process. And, finally, the pragmatic step focuses on the use of the product.

The border represents a line dividing parts, a defined limit.

DHM and Posturography. https://doi.org/10.1016/B978-0-12-816713-7.00053-2
Copyright © 2019 Elsevier Inc. All rights reserved.

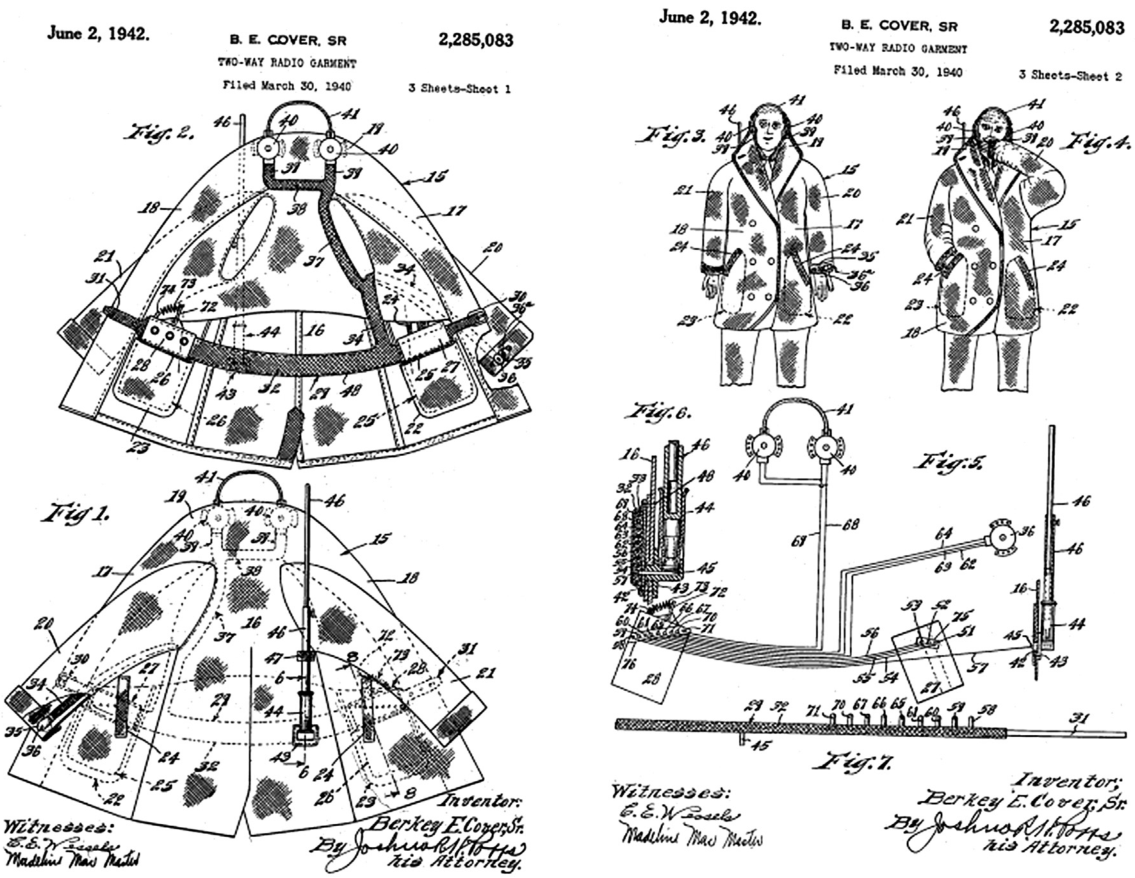


FIGURE 53.1 Cover (1942). Two-way radio garment, Patent N. US2285083A.

As stated in the Oxford dictionary, "border" is "the edge or boundary of something, or the part near it." Being physical or virtual, material or metaphoric, borders are liminal spaces where two or more parts meet each other. In this sense, a bordering line is a place where divisions become opportunities of encounter. According to this perspective, there are three different ways of decoding borders through research in design: extending, passing through, and blurring.

Each approach assumes that borders are limits but can provide opportunities to foster a mutual exchange between the parts they divide. "Passing through" can be used to define the concept of "passing through the fabric." To pass through the borders, the electronics and the textile create a connection between two areas. Definition of "passing through" is (1) moving from one area (A) to another (B) and (2) creating a connection between these two or more areas. The border is remaining. But our action is affecting its form.

The interaction of the two borders, the electronics and the textile, opens new frontiers (a line of the borders) in the applied and human factor field.

The interaction can be active (can sense and react to the condition or stimuli), passive (can only sense the environmental conditions or stimuli), and very smart (can sense, react, and adapt themselves accordingly) (Tao, 2001).

Smart clothing meets the synthetic or design process defining the design requirements. Those are translated into properties that are achieved through material fabrication technologies by applying design parameters.

The requirements are represented by the functionality, the usability, the durability, the shape conformability, connectivity, and affordability of the smart product (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019).

Wearability also plays an important role in design. Gemperle, Kasabach, Stivoric, Bauer, & Martin (1998) defined 13 points as guidelines to design for wearability, such as the placement of the sensor, the form language (shape), the dynamic structure, the proxemics (human perception of the space), the sizing (for body diversity), the attachment, the containment (considering inside the form), the weight (as it spreads across the human body), the accessibility (physical access to the form), the sensor interaction (for passive or active input), the thermal, the esthetics, and finally the long-term use (effect on the body and mind).

The design requirements and properties are gained by the materials and fabrication technologies.

These requirements are introduced in standards such as the IEC TC 124 (www.iec.ch) in the field of wearable electronic devices and technologies.

In fact, bioelectric signals are achieved through textrodes (textile electrodes) that are constituted of electrically conductive yarns that can be in contact with the skin. It can be distinguished metal yarns (stainless steel, copper, or silver mixed with natural or synthetic fibers) and yarns containing electro-conductive fibers (polymeric or carbon-coated threats). In that case, the textrodes do not require gel, as this effect can be obtained through the sweat (transpiration).

Today the smart clothing era is creating a healthcare community capable of encroaching into new territories and compiling a more complete picture of the analyzing group, including different geographies or specifics diagnosis, in terms of health and safety.

They are covering different areas of applications such as sport, wellness, entertainment and leisure, fashion, space, protection, safety, and military. Smart clothing is becoming the science and technology frontier for the future, in particular for the last three areas.

Scataglini, Andreoni, and Gallant (2015) classified the main current applications of smart clothing in the military field in health monitoring, environmental safety monitoring, stress management, and empowering human function. Smart fabric is capable of detecting the health status of the subject (heart rate, breathing rate, body temperature, blood oxygen saturation, position, activity, and posture), external information, and an alert.

Smart clothing technology together with environmental and performance data provides a detailed real-time feedback from the wearers monitoring their physical function and recording changes in ability over time.

Stress, training, fatigue, and environmental conditions have a great influence on human-machine-environmental system performance. Combining data from the different components of the system is mandatory.

The design of smart clothing is crucial to obtain the best results (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019). Identifying all the steps involved in functional design clothing workflow can prevent a decrease in wearer's performance, ensuring a more successful design (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019). Smart clothing represents a "second skin" that has a close "intimate" relation with the human body. The relation is physiological, psychological, biomechanical, and ergonomic (Fig. 53.2).

Effectiveness of functional wear is based on the integration of all these considerations into the design of a smart clothing system (Fig. 53.3). The design process begins through the analysis of the anticipated user and the identification of the end-user needs. Design and technological issues are the two main macro areas involved in the process together with the

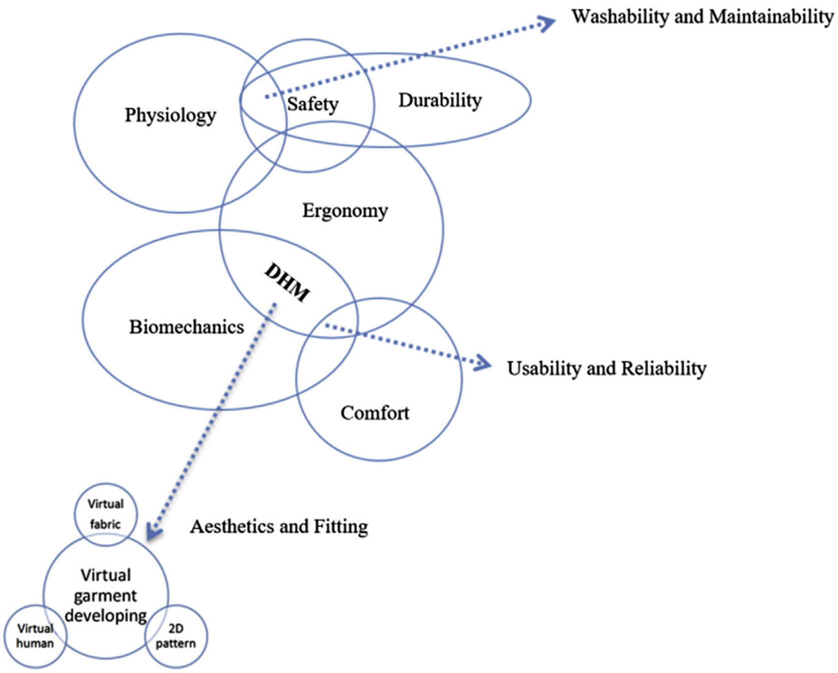


FIGURE 53.2 Smart clothing design requirements map.

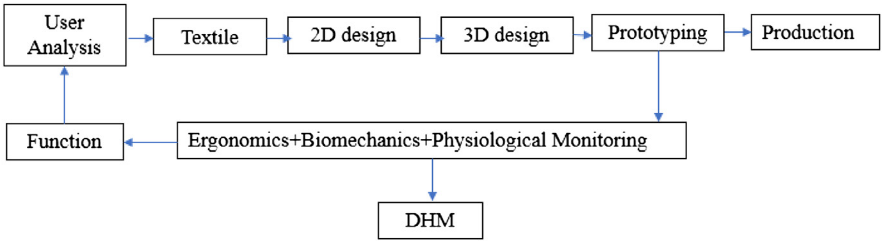


FIGURE 53.3 Garment co-design workflow.

esthetical one (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019). Once these criteria have been established, the initial esthetic design is created within the framework of the user's needs (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019). Design decisions are evaluated and reevaluated based on physiological, ergonomic, and biomechanical monitoring of the wearer's performance (Scataglini et al., 2017). This evaluation can be visualized and simulated in digital human model (DHM). Therefore, alternative solutions are generated for each decision. Alternatives are then evaluated on a weighted scale to arrive at the best solution or combination of solutions for each decision (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019).

Iterative co-design steps are used to influence the modifications made in the next prototype and then the design process begins again. This ensures that corrections have been made before the design is finalized. When resources permit, multiple designs will be compared with each other to examine the strengths and weaknesses of each.

The aim of this chapter is to outline the requirements and the steps for the design of the smart garment and the evaluation process for testing the smart garment using Digital Human Modeling.

2. Functional evaluation

The evaluation of functioning can be done with biomechanical, ergonomic, and physiological requirements of the end user during different tasks. The physiological evaluation is specifically related to the position of the garment and the adherence ("fit") of the textile to the body, while the biomechanics and ergonomics deal with the thermal discomfort and agility.

2.1 Combining accelerometer and physiological data for activity and design evaluation

Once the technical and esthetical details of the cut and the proportion of the initial garment prototypes have been fitted, the next step is the introduction of smart technology into the garment. Normally, co-designers meet for evaluating the functional design process that integrates embedded sensors into the cloth.

Heart rate variability (HRV) is a physiological measurement of the autonomic activity of the heart (ChuDuc, NguyenPhan, & NguyenViet, 2013). The autonomic nervous system (ANS) actively compensates for injury or fatigue by modulating the balance between parasympathetic and sympathetic cardiovascular control mechanisms (Scataglini, 2017). HRV is the physiological phenomenon of variation in the time interval between heartbeats. It is measured by the variation of the beat-to-beat interval and its frequency analysis (ChuDuc et al.2013).

Methods to detect heart beat include ECG, blood pressure, ballistocardiography (Bertson et al.1997; Brüser, Stadlthanner, De Waele, & Leonhardt, 2011; McCraty & Shaffer, 2015) , and the pulse signal derived from a photoplethysmograph.

Other terms include "cycle length variability," where R represent the peak of the QRS complex of the ECG wave. RR represents the interval between successive R. Sometimes the term RR is replaced by NN meaning that the beats are normal. To detect changes over a period of hours requires a large volume of data to be collected and analyzed. Holter device can record the ECG in subjects from 24 h to weeks. Smart clothing revealed to be a good alternative for physiological monitoring (Vojtech, Bortel, Neruda, & Kozak, 2013). The smart clothing for monitoring subject's physiological status is based on the integration of wearable textile electrode ("textrode") technology for ECG measurements (Fig. 53.4) in a plurality of configurations and leads according to the user's anthropometry and task requirements.

HRV measurements in time and frequency domain were extrapolated through a MATLAB algorithm that works offline on time intervals between successive heartbeats from ECG recordings collected by the two textrodes embedded in the cloth (Scataglini et al., 2017). The innovative marks of the study stem not only from the ability to optimize the evaluation in terms of human resources and in a noninvasive way for humans but also from the possibility to implement a new assessment for the evaluation of subject's physiological status (Scataglini et al., 2017).

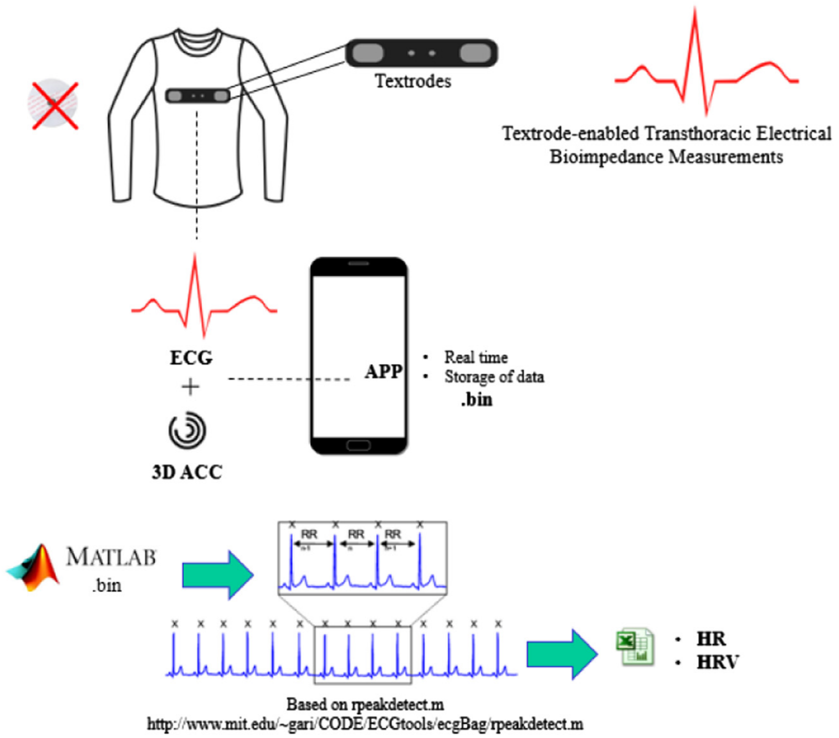


FIGURE 53.4 The smart shirt system.

Two textrodes made by conductive material and can be embedded into the clothes enabling transthoracic electrical bioimpedance measurements. Two snaps can be used to provide the connection between the shirt and the hardware unit (Fig. 53.4).

A MATLAB function rpeakdetect.m (Pan & Tompkins, 1985) written by G. Clifford (gari@ieee.org) and made available under the GNU public license can be used to extract the heart rate. This function used a batch QRS detector based on the one proposed by Hamilton & Tompkins, 1986. This solution allows to detect the QRS complex and to identify the R-peak occurrence.

HRV can be assessed with various analytical approaches, although the most common are the time domain and frequency domain analysis. An example of a Matlab program that was created to process all the measurements is shown in Fig. 53.5. Heart rate and HRV can be exported as an excel file for further analysis.

According to HRV measurements defined by Malik et al (1996), Vollmer (2015), the SDNN (standard deviation of the successive RR) (53.1) and the RMSSD (root mean square of the sum of successive differences between adjacent RR intervals) (53.2), time domain parameters can be calculated.

$$SDNN = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(RRi - RR)^2} \tag{53.1}$$

$$RMSSD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(RR_{i+1} - RR_i)^2} \tag{53.2}$$

SDNN reflects all the cyclic components (i.e., short-term and long-term) that are responsible for variability in the period of recording.

Normally it is calculated over a 24 h period. As the period of monitoring decreases, SDNN estimates shorter cycle lengths. It should also be noted that the total variance of HRV increases with the length of analyzed recording. RMSSD is calculated as an index of vagus nerve−mediated cardiac control, which takes respiratory sinus arrhythmia (Berntson et al. 2005).

Frequency domain analysis describes high and low frequency rates of variability changes, corresponding to the activity of the ANS.

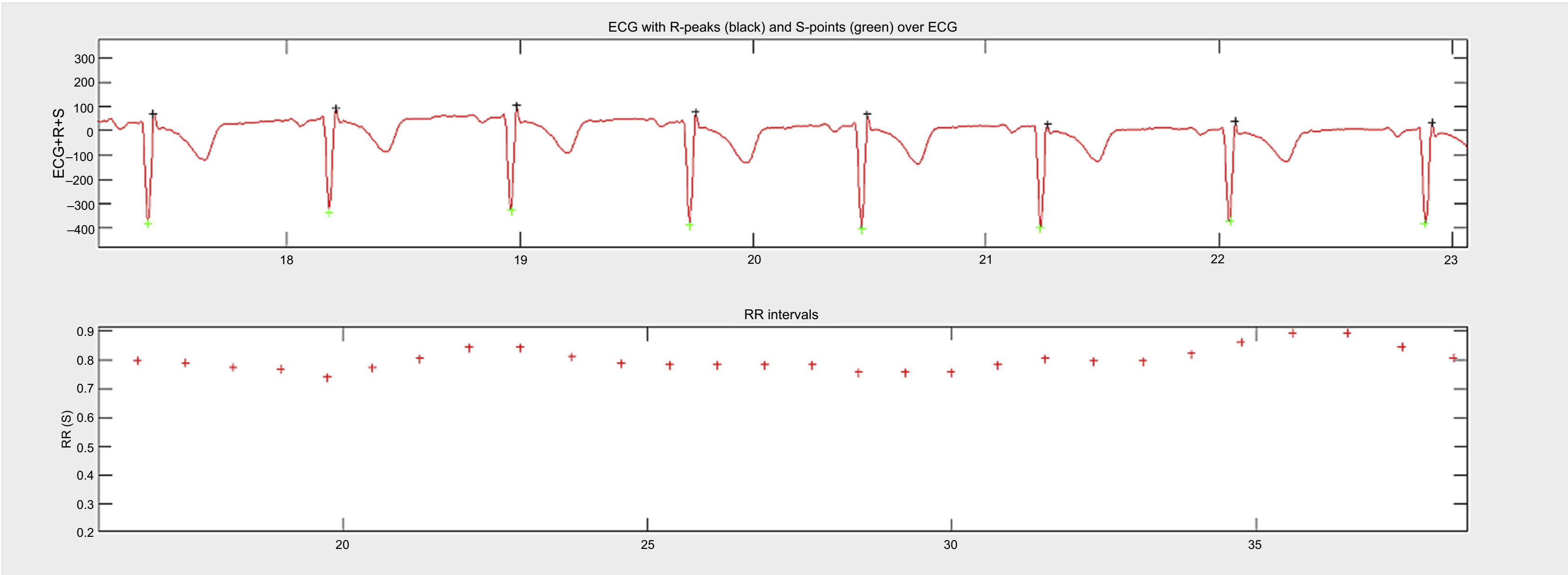


FIGURE 53.5 ECG data extrapolation.

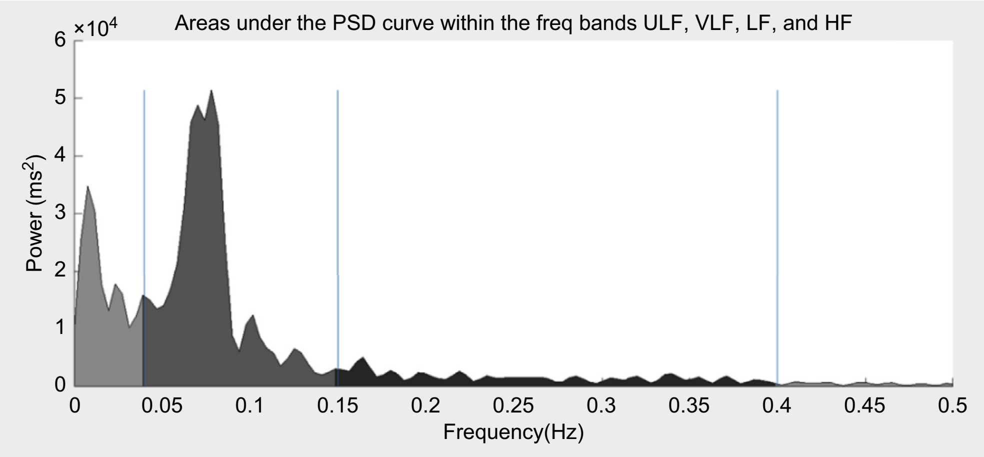


FIGURE 53.6 Relative power spectra density.

The high-frequency power (HF), (0.15−0.4 Hz), is a marker of parasympathetic activity; the low frequency power (LF), (0.04−0.15 Hz), is a marker of parasympathetic and sympathetic activity. Very low frequency power (VLF) (0.003−0.04 Hz) equates to rhythms or modulations with periods that occur between 25 and 300 s. Although all 24-hour clinical measurement of HRV reflecting low HRV is linked with increased risk of adverse outcomes, the VLF band has stronger associations with all-cause mortality than LF and HF band. Low VLF power has been shown to be associated with arrhythmic death and post-traumatic stress disorders (PTSD).

The ultralow frequency component (ULF), $\leq$0.003 Hz, can also be used to analyze the sequence of NN intervals in the entire 24-hour period. The result then includes an ULF component, in addition to VLF, LF, and HF components (Fig. 53.6) (Scataglini et al., 2017).

The ratio of LF/HF (53.3) represents the sympathovagal balance or the sympathetic modulations (Fig. 53.7).

$$\frac{LF}{HF} = \frac{\int_{0.04\ Hz}^{0.15 Hz} F(\lambda)\mathrm{d}\lambda}{\int_{0.15\ Hz}^{0.40\ Hz} F(\lambda)\mathrm{d}\lambda} \tag{53.3}$$

Endurance and training induces an elevated parasympathetic modulation over 24-hour recording period (higher RMSSD and HF and lower LF/HF ratio) (Dong, 2016).

Minassian et al. (2015) investigated the association of predeployment HRV with risk of postdeployment PTSD in active-duty marines. After accounting for deployment-related combat exposure, lower HRV before deployment as measured by an increased LF to HF ratio of HRV was associated with risk of PTSD diagnosis after deployment. The prevalence of postdeployment PTSD was higher in participants with high predeployment LF/HF ratios (15.8% of 38 participants) compared with participants who did not have high LF/HF ratios. HRV indexes both peripheral and central

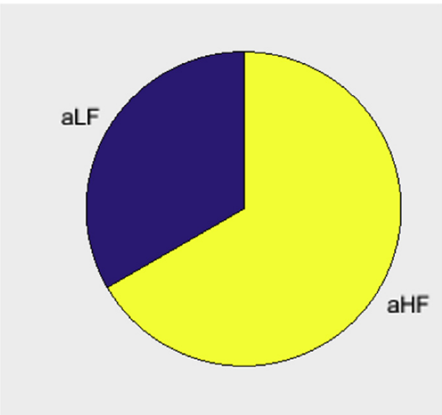


FIGURE 53.7 Ratio of low frequency (LF)/high frequency (HF).

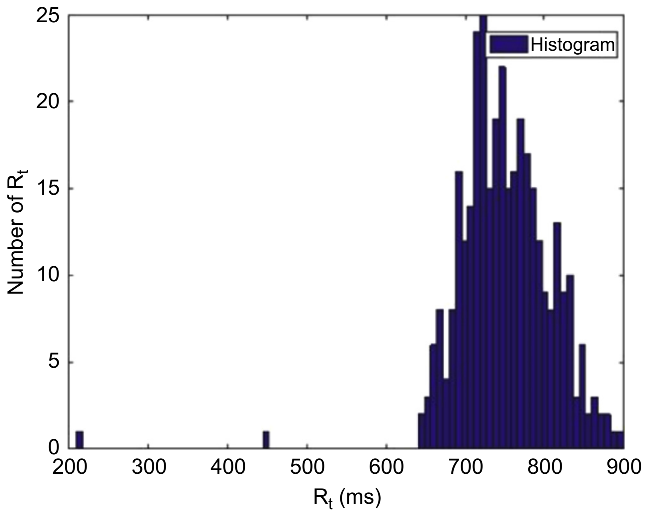


FIGURE 53.8 Histogram.

activity of the five parasympathetic and sympathetic nervous systems. Mäntysaari et al. (2005) evaluated the usefulness of HRV for monitoring the soldiers' physiological status during a 19-day ranger training operation. HRV analysis based on data collection made in the field by the soldiers themselves is not a robust enough method to monitor the physiological status of soldiers. Both the time and frequency domain analysis of HRV require an ECG recording that is quite free from artifacts and technical disturbance and with a stable baseline. These requirements are difficult to be met in the field because the soldier should be able to rest in calm conditions at least for 5 min to obtain acceptable HRV data. It seems to us that the studies of HRV analysis for monitoring the physiological condition of a soldier should be directed to more technical tasks, in which the optimal conditions for data collection can be achieved.

Another method is the geometrical one, based on a histogram of RR intervals with a bin size of 1/128 s. The HRV triangular index (53.4) is given by the most frequent value X (mode) with the absolute frequency k (Malik et al., 1996):

$$\text{HRV triangular index} = n/k \tag{53.4}$$

A triangular interpolation of the discrete distribution of RR intervals (histogram counts) (Fig. 53.8) is used for the TINN measures (53.5):

$$\text{TINN} = \text{M} - \text{N} \tag{53.5}$$

where M and N are the vertices of the triangular function T, with T (t) $= 0$ for t $\leq$ N and t $\geq$ M. The modal bin is identical to the sample distribution T(X) $=$ k. T receives the values of a linear function by connecting (N,0) with (X, k) and (X, k) with (M,0). The triangular function with the best fit to the sample distribution defines M and M.

HRV can be also measured using the return map of RR intervals "Poincaré plot" (Fig. 53.9) as ratio of the standard deviation SD2 along the identity line ($RR_{i+1=}RR_i$) and the standard deviation SD1 along the perpendicular axis ($RR_{i+1=-}RR_i$) (Malik et al. 1996). The SD1 is based on "short-term HRV," while SD2 on the "long-term HRV."

The smart garments can be tested to evaluate the signal reliability with respect to skin motion artifacts. Standoli et al. (2016) defined a signal reliability protocol that consists of eight physical exercises. An example of the reliability protocol figure wearing a smart clothing is shown in Fig. 53.10.

2.2 Ergonomic and biomechanical evaluation

Prototyping is an important step for garment design or apparel design that affects the ergonomic characteristics of physical, psychological, and functional together with esthetical one. Therefore, the standardization of micro/macro environment factors in garment design is important, providing an example of how to design garment at the prototyping stage (Scataglini et al.2017). The clothing prototyping for an individual can be done conventional (traditional) and virtually (Fig. 53.11) in software like (Blender Online Community, 2015).

The patternmaker drafts the paper pattern onto a plain fabric. The drape is thoroughly reviewed by the patternmaker and the designer.

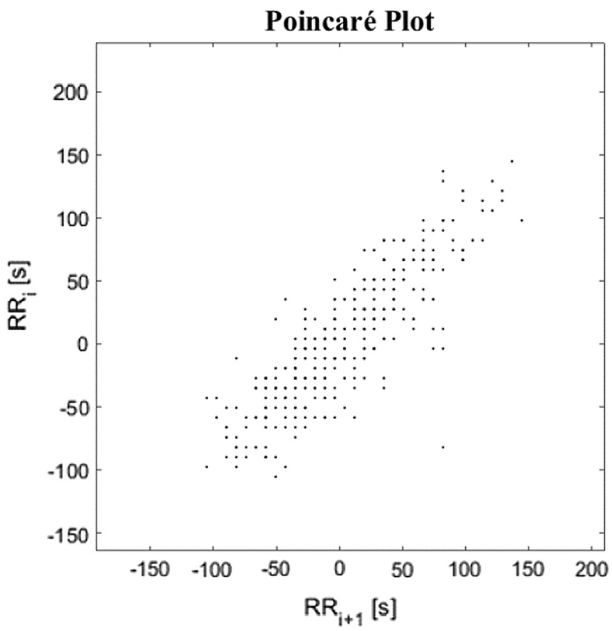


FIGURE 53.9 Poincaré plot.

Each garment pattern needs to have the style number, the name of the part, the balance mark, and the construction lines. The successive step can be to digitize it to turn the draft into a computer-aided design CAD/CAM.

Virtual garment development involves three main actors: virtual human or DHM, 2D pattern, and a virtual fabric (Fig. 53.12).

This relation between them can be from 2D to 3D and 3D to 2D (Fig. 53.13).

2D → 3D: The 2D pattern pieces from the 3D CAD software are added to virtualization software (e.g., Blender Online Community, 2015) to use it for the virtual try-on on a virtual human.

3D → 2D → 3D: It consists of designing 3D garments around a virtual human. Regarding that the 3D garment can be unwrapped in 2D pattern.

Fashion designers draw fashion illustrations and garment flats to design the concept, while patternmakers design patterns by measuring anthropometric dimensions of the end user. Communication between patternmakers and fashion designers is often lacking. As a consequence, the process is time-consuming and does not take into account what the user thinks about it.

Virtual garment design helps to understand the ergonomic characteristics of physical, psychological, and functional together with esthetical one of the end user. In fact, the main advantages of 3D garment prototyping are as follows:

- eliminate the sewing process during the prototyping
- reduce the materials and save time for prototyping
- quick response time on design changes
- personalized garment

The disadvantages are as follows:

- no representation of the fabric behavior properties
- fitting of the garment on virtual models
- model physical based
- customization of parametric model

Body shape is the major factor that influences the fit and satisfaction with clothing (Luible & Magnenat-Thalmann, 2008). Statistical shape modeling (SSM) is an intuitive approach to map out body shape variability of a 3D body shape database (Danckaers et al., 2014, 2018, 2019). The shape variance is described by shape parameters, which can be adapted to form a new realistic shape. Furthermore, body shapes belonging to a specific percentile of a target group can be visualized. SSM can intervene to the disadvantages mentioned earlier, creating a link between the end user and the apparel designer.

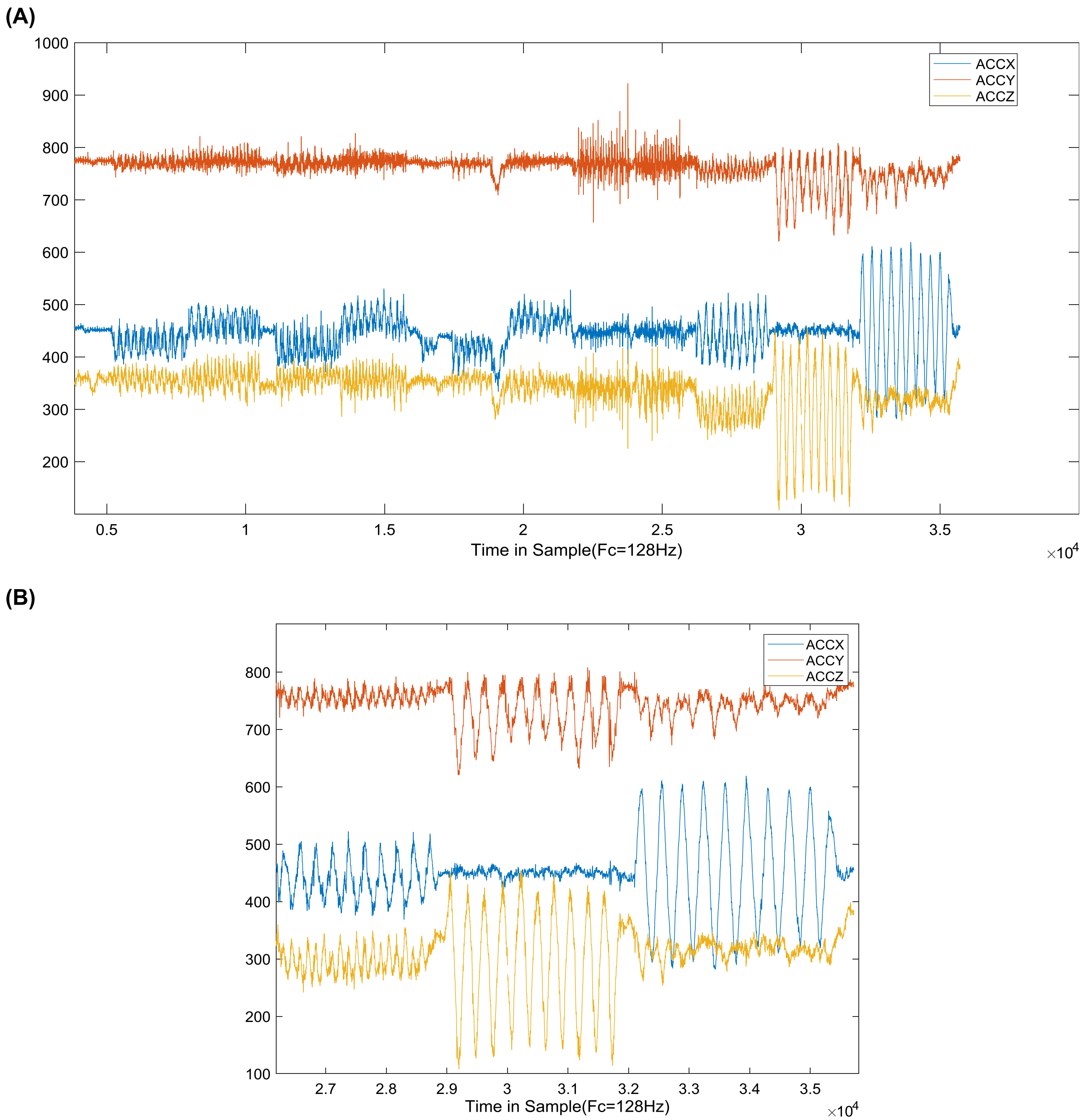


FIGURE 53.10 An example of signal reliability protocol that consists of eight physical exercises recorded through a trunk-worn 3-axial accelerometer integrated into a smart clothing (A = all the protocol, B = three exercises (10 repetitions each)).

FIGURE 53.11 Clothing prototyping traditional (on the left) and virtual (on the right).

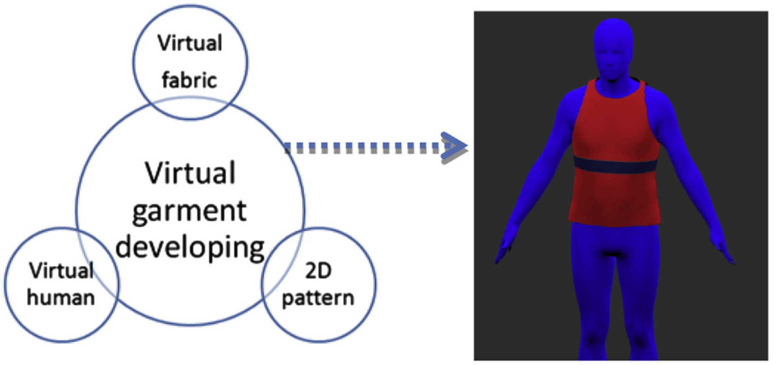


FIGURE 53.12 Virtual garment developing.

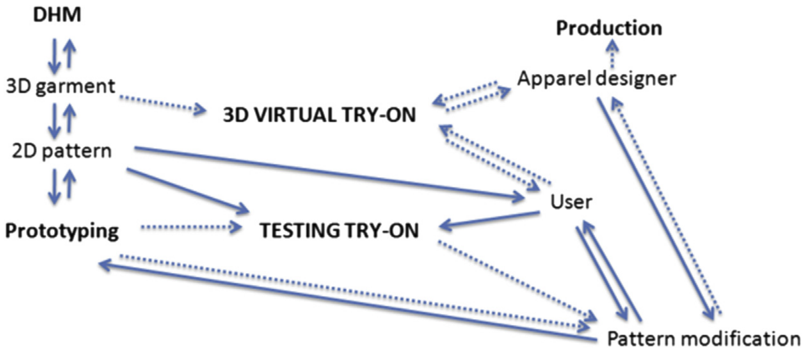


FIGURE 53.13 Apparel design workflow.

An SSM is a valuable tool for product designers, as it captures the variability of body geometry of a population. SSMs are built from 3D scans of a population of shapes. Therefore, they contain much more information than traditional anthropometrical measurements. SSMs are highly valuable for product designers because ergonomic products for a specific target population can be designed from these models. By adapting the parameters of the SSM, a new realistic shape can be formed. Product developers may exploit SSMs to design virtual design mannequins and explore the body shapes belonging to a specific percentile of a target group, for example, to visualize extreme shapes. Moreover, an SSM allows to simulate a specific 3D body shape (Park & Reed, 2015), which is useful for customization in a (possibly automated) workflow.

The innovative approach we propose concerns a combination of different digital technologies and applications to create a common co-design workflow for the design of a garment implemented in Blender Online Community (2015).

Human activities can then be replicated based on body shape and motion data collected on a subject by a mocap system (Scataglini et al., 2017, Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019). This provides a visualization of a DHM based on anthropometry and biomechanics of the subject (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019).

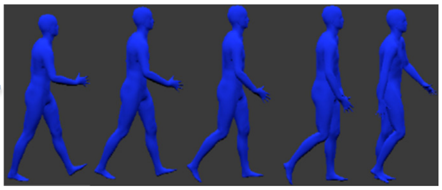
The co-design workflow describes all the steps necessary to simulate garment fitting and esthetics in Blender according to Scataglini, Andreoni et al. (2019), Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers (2019), Scataglini et al. (2019) and can be resumed in these steps (1−13) (Fig. 53.14). In particular, steps 1−7 are necessary to arrive to the kinematical model. However, steps 8−13 are necessary to dress up the model and to simulate garment fitting and esthetics (Figs. 53.14 and 53.15).

A clustering algorithm can be used to determine a sizing system based on the biometrics features of the subject (Scataglini, Andreoni et al., 2019, Scataglini, Danckaers, Haelterman, Huysmans, & Sijbers, 2019, Scataglini et al., 2019). Considering a population, the smart shirt or vest meshes can be calculated from the anthropometric clustering evaluation according to Daanen et al., 2018; ISO 8559-2(2017).

For every cluster, a body shape can be simulated from those specific body dimensions (Fig. 53.16). This procedure allows to determine the number of clusters that best describes the population.

From SSM to Kinematical model

1) Creation of SSM
2) Importing the SSM into Blender as OBJ file.
3) Importing the skeleton from a Mocap system into Blender as OBJ file.
4) Parenting the SSM with the skeleton.
5) Re-importing the skeleton as BVH file.
6) Retargeting
7) Kinematical model



Kinematical model

DHM_Dressing up

8) Creating the shirt mesh
9) UV mapping your mesh
10) Rigging the shirt mesh on the Kinematic model
11) Smart clothing on the kinematic model
12) Clothing simulation in Blender
13) Clustering algorithm

FIGURE 53.14 Garment co-design workflow in Blender.

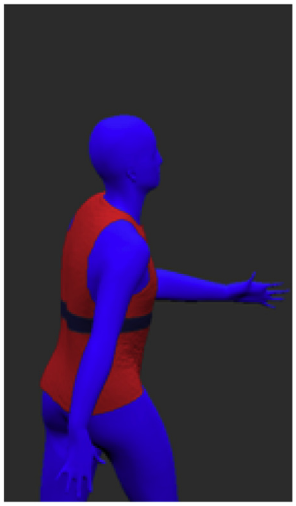


FIGURE 53.15 Clothing simulation in Blender.

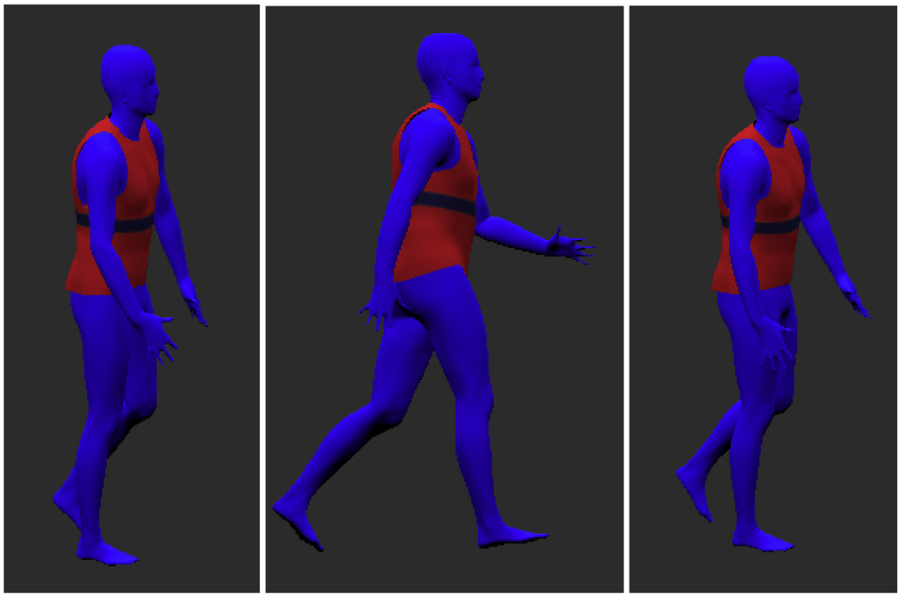


FIGURE 53.16 Moving SBSM with clothing in Blender.

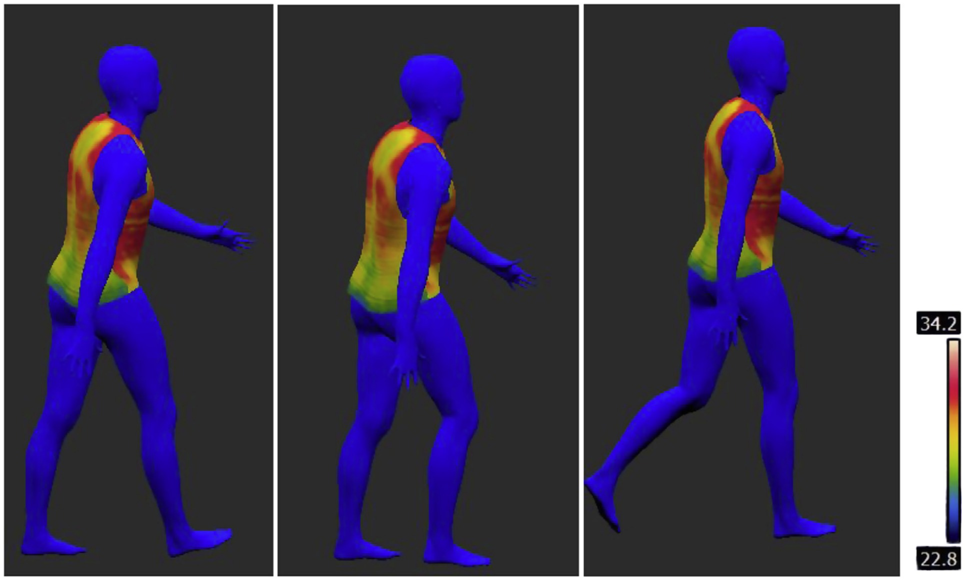


FIGURE 53.17 Thermal Imaging in Moving SBSM with clothing in Blender(sagittal-posterior).

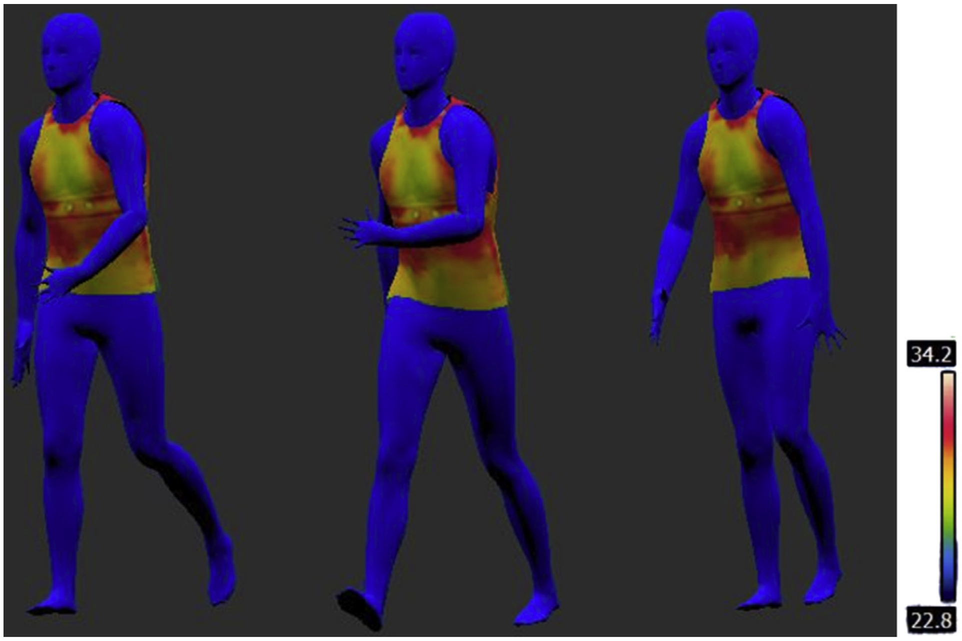


FIGURE 53.18 Thermal Imaging in Moving SBSM with clothing in Blender(sagittal-anterior).

More attention should to be paid to understanding ergonomic issues, heat stress implications, and the relationship between the task and the clothing (Scataglini et al., 2017). The degree of thermophysiological comfort is defined by the thermalphysiological characteristics of the textile and a range of motion while we are performing a task. Starting from this assumption, the thermophysiological wear comfort can be evaluated using a thermal image from an FLIR camera (FLIR, Wilsonville, OR, USA, with an infrared resolution of 4800 pixels, MSX resolution 320 × 240, thermal sensitivity below 0.15°C, and accuracy of ±2°C) applied on the DHM (Figs. 53.17 and 53.18).

2.2.1 Clothing simulation

Later, the cloth mesh is rigged with the SSM creating a kinematic model. The next step is the simulation of the clothing in Blender (Villar, 2014) (Fig. 53.19).

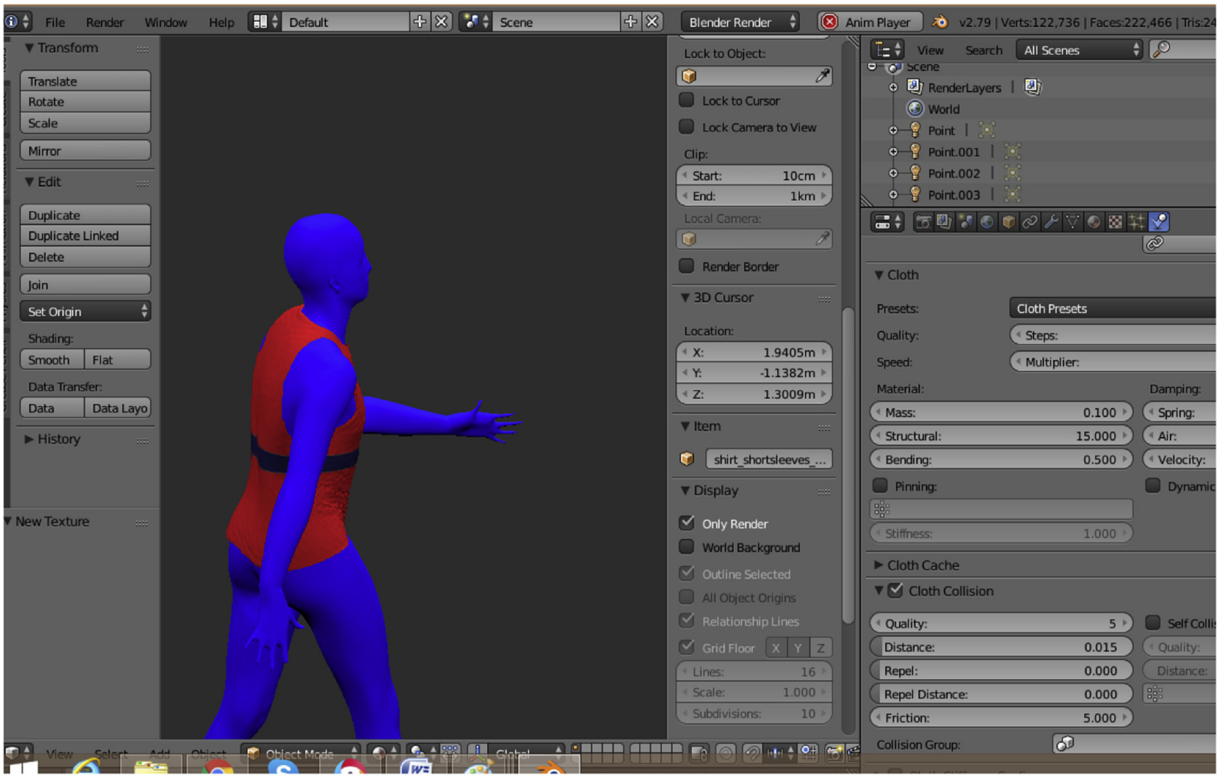


FIGURE 53.19 Clothing simulation.

In fact, Blender has a "physics tab" in the properties windows that includes a function called "cloth" This function contains different options such as cloth materials (mass, structural, and bending), collisions, cloth field weights, cloth stiffness scaling, and clothing springs.

Below is represented an example of clothing simulation setting the cloth material (e.g., cotton) with a self-collision applying a cloth field weights on the texture.

3. Conclusion

This chapter presented all the steps necessary in the co-design workflow for garment design using DHM as supporting tool in user-centered design for smart clothing.

Physiological, biomechanical, and ergonomic aspects represent a retro-feedback of the user's function in the iterative co-design workflow for design of smart garment, permitting the redesign and the technological refinement of it. In this iteration, Digital Human Modeling demonstrated to be a valid tool for the design of smart technology preventing a decrease of the wearer's performances ensuring a more successful design.

Acknowledgments

This work was supported by the Agency for Innovation by Science and Technology in Flanders (IWT-SB 141520). We would also like to thank all the participants in this study.

References

Berntson, G. G., Bigger, J. T., Eckberg, D. L., Grossman, P., Kaufmann, P. G., Malik, M., … Van Der Molen, M. W. (1997). Heart rate variability: Origins, methods, and interpretive caveats. *Psychophysiology, 34*(6), 623–648. https://doi.org/10.1111/j.1469-8986.1997.tb02140.x.

Blender Online Community. (2015). *Blender-A 3D modeling and rendering package*. Retrieved from https://blendermarket.com/.

Brüser, C., Stadlthanner, K., De Waele, S., & Leonhardt, S. (2011). Adaptive beat-to-beat heart rate estimation in ballistocardiograms. *IEEE Transactions on Information Technology in Biomedicine, 15*(5), 778–786. Retrieved from https://www.researchgate.net/profile/Stijn_De_Waele/publication/50595045_Adaptive_Beat-to-Beat_Heart_Rate_Estimation_in_Ballistocardiograms/links/54bd1d050cf218d4a16a042b.pdf.

Cho, G. (2009). *Smart clothing: Technology and applications*. Boca Raton: CRC Press.

ChuDuc, H., NguyenPhan, K., & NguyenViet, D. (2013). A review of heart rate variability and its applications. *APCBEE Procedia, 7*(2013), 80–85. https://doi.org/10.1016/j.apcbee.2013.08.016.

Cover, B. E. (1942). *Two-way radio garment*. Patent N.US2285083A. Chicago, USA.

Daanen, H. A. M., & Psikuta, A. (2018). 3D body scanning. In R. Nayak, & R. Padhye (Eds.), *Automation in garment manufacturing* (pp. 237–252). Woodhead Publishing. https://doi.org/10.1016/B978-0-08-101211-6.00010-0.

Danckaers, F., Huysmans, T., Hallemans, A., De Bruyne, G., Truijen, S., & Sijbers, J. (2018). Full body statistical shape modeling with posture normalization. In D. Cassenti (Ed.), *Advances in human factors in simulation and modeling: Proceedings of the HFE 2017 international conference on human factors in simulation and modeling, July 17–21, 2017, The Westin Bonaventure hotel, Los Angeles, California, USA* (pp. 437–448). Springer, Cham.

Danckaers, F., Huysmans, D., Ledda, A., Verwulgen, S., Van Dogen, S., & Sijbers, J. (2014). Correspondence preserving elastic surface registration with shape model prior. In *Paper presented at 2014 22nd international conference of pattern recognition, Stockholm, Sweden*. Retrieved from https://ieeexplore.ieee.org/abstract/document/6977085.

Danckaers, F., Scataglini, S., Haelterman, R., Van Tiggelen, D., Huysmans, T., & Sijbers, J. (2019). Automatic generation of statistical shape models in motion. In D. Cassenti (Ed.), *Advances in intelligent systems and computing: Vol. 780. Advances in human factors in simulation and modeling. AHFE 2018* (pp. 170–178). Cham: Springer.

Dong, J. G. (2016). The role of heart rate variability in sport physiology. *Experimental and Therapeutic Medicine, 11*(5), 1531–1536.

Gemperle, F., Kasabach, C., Stivoric, J., Bauer, M., & Martin, R. (1998). Design for wearability. In *Paper presented at 2nd IEEE international symposium on wearable computers, Pittsburgh, USA*. Retrieved from https://doi.org/10.1109/ISWC.1998.729537.

Hamilton, P., & Tompkins, W. (1986). Quantitative investigation of QRS detection rules using the MIT/BIH arythmia database. *IEEE Transactions on Biomedical Engineering, 33*(12), 1157–1165. https://doi.org/10.1109/TBME.1986.325695.

International Standards Organisation. (2017). *Size designation of clothes – Part 2: Primary and secondary dimension indicators (ISO 8559-2:2017)*. Retrieved from https://www.iso.org/standard/64075.html.

Luible, C., & Magnenat-Thalmann, N. (2008). The simulation of cloth using accurate physical parameters. In D. Thalmann (Ed.), *CGIM '08 proceedings of the tenth IASTED international conference on computer graphics and imaging* (pp. 123–128). California, USA: ACTA Press Anaheim. Retrieved from https://dl.acm.org/citation.cfm?id=1722328.

Malik, M., Camm, A. J., Bigger, J. T., Breithardt, G., Cerutti, S., Cohen, R. J., … Singer, D. H. (1996). Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. *European Heart Journal, 17*(3), 354–381. Retrieved from https://moh-it.pure.elsevier.com/en/publications/heart-rate-variability-standards-of-measurement-physiological-int.

Mäntysaari, M., Kyröläinen, H., Hämäläinen, H., Karinkanta, J., Santtila, M., & Koski, H. (2005). Heart rate variability analysis based on recordings made by soldiers in field conditions during a 19-day ranger training operation. In *Strategies to maintain combat readiness during extended deployments – a human systems approach* (pp. 17-1–17-4). Meeting Proceedings RTO-MP-HFM-124, Paper 17. Neuilly-sur-Seine, France: RTO. Retrieved from: https://www.sto.nato.int/publications/.../RTO-MP-HFM-124/MP-HFM-124-17.pdf.

Mattila, H. R. (2006). *Intelligent textiles and clothing* (1st ed.). Woodhead Publishing.

McCraty, R., & Shaffer, F. (2015). Heart rate variability: New perspectives on physiological mechanisms assessment of self-regulatory capacity, and health risk. *Global Advances in Health and Medicine, 4*(1), 46–61. https://doi.org/10.7453/gahmj.2014.073.

Minassian, A., Maihofer, A. X., Baker, D. G., Nievergelt, C. M., Geyer, M. A., & Risbrough, V. B. (2015). Association of predeployment heart rate variability with risk of postdeployment posttraumatic stress disorder in active-duty marines. *JAMA Psychiatry, 72*(10), 979–986. https://doi.org/10.1001/jamapsychiatry.2015.0922.

Pan, J., & Tompkins, W. (1985). A real-time QRS detection algorithm. *IEEE Transactions on Biomedical Engineering, BME-32*(3), 230–236. Retrieved from https://www.robots.ox.ac.uk/~gari/teaching/cdt/A3/readings/ECG/Pan+Tompkins.pdf.

Park, S., & Jayaraman, S. (2003). Enhancing the quality of life through wearable technology. *IEEE Engineering in Medicine and Biology Magazine, 22*(3), 41–48. https://doi.org/10.1109/MEMB.2003.1213625.

Park, B., & Reed, & M. P. (2015). Parametric body shape model of standing children aged 3-11 years. *Ergonomics, 58*(10), 1714–1725. https://doi.org/10.1080/00140139.2015.1033480.

Scataglini, S. (2017). *Ergonomics of gesture: Effect of body posture and load on human performance*. PhD thesis. Retrieved from http://hdl.handle.net/10589/136840.

Scataglini, S., Andreoni, G., & Gallant, J. (2015). A review of smart clothing in military. In *WearSys '15 proceedings of the 2015 workshop on wearable systems and applications* (pp. 53–54). New York, USA: ACM.

Scataglini, S., Andreoni, G., & Gallant, J. (2019a). Smart clothing design issues in military applications. In T. Ahram (Ed.), *Advances in intelligent systems and computing: Vol. 795. Advances in human factors in wearable technologies and game design. AHFE 2018* (pp. 158–168). Cham: Springer.

Scataglini, S., Danckaers, F., Haelterman, R., Huysmans, T., & Sijbers, J. (2019b). Moving statistical body shape models using blender. In S. Bagnara, R. Tartaglia, S. Albolino, T. Alexander, & Y. Fujita (Eds.), *Advances in intelligent systems and computing: Vol. 822. Proceedings of the 20th congress of the international ergonomics association (IEA 2018). IEA 2018* (pp. 28–38). Cham: Springer.

Scataglini, S., Danckaers, F., Haelterman, R., Huysmans, T., Sijbers, J., & Andreoni, G. (2019c). Using 3D statistical shape models for designing smart clothing. In S. Bagnara, S. Albolino, T. Alexander, & Y. Fujita (Eds.), *Advances in intelligent systems and computing: Vol. 822. Proceedings of the 20th congress of the international ergonomics association (IEA 2018). IEA 2018* (pp. 18–27). Cham: Springer.

Scataglini, S., Truyen, E., Perego, P., Gallant, J., Tiggelen, D. V., & Andreoni, G. (2017). Smart clothing for human performance evaluation: Biomechanics and design concepts evolution. In S. Wischniewski, & T. Alexander (Eds.), *Proceedings of the 5th international digital human modeling symposium* (pp. 9−17). Dortmund, Germany: Federal Institute for Occupational Safety and Health.

Standoli, C. E., Guarneri, M. R., Perego, P., Mazzola, M., Mazzola, A., & Andreoni, G. (2016). A smart wearable sensor system for counter-fighting overweight in teenagers. *Sensors, 16*(8), 1220. https://doi.org/10.3390/s16081220.

Stoppa, M., & Chiolerio, A. (2014). Wearable electronics and smart textiles: A critical review. *Sensors, 14*(7), 11957−11992. https://doi.org/10.3390/s140711957.

Tao, X. (2001). Smart fibres, fabrics and clothing: Fundamentals and applications. In *Woodhead publishing series in textiles*.

Villar, O. (2014). *Learning blender: A hands on guide to creating 3D animated characters* (2nd ed.). New Jersey, USA: Addison Wesley.

Vojtech, L., Bortel, R., Neruda, M., & Kozak, M. (2013). Wearable textile electrodes for ECG measurement. *Advances in Electrical and Electronic Engineering, 11*(5), 410−414. https://doi.org/10.15598/aeee.v11i5.889.

Vollmer, M. (2015). A robust, simple and reliable measure of heart rate variability using relative RR intervals. In A. Murray (Ed.), *Computing in cardiology conference 2015 (CinC)* (pp. 609−612). Computing in Cardiology.