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Research Article

Multiobjective Design of Wearable Sensor Systems for Electrocardiogram Monitoring

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Wearable sensor systems will soon become part of the available medical tools for remote and long term physiological monitoring. However, the set of variables involved in the performance of these systems are usually antagonistic, and therefore the design of usable wearable systems in real clinical applications entails a number of challenges that have to be addressed first. This paper describes a method to optimise the design of these systems for the specific application of cardiac monitoring. The method proposed is based on the selection of a subset of 5 design variables, sensor contact, location, and rotation, signal correlation, and patient comfort, and 2 objective functions, functionality and wearability. These variables are optimised using linear and nonlinear models to maximise those objective functions simultaneously. The methodology described and the results achieved demonstrate that it is possible to find an optimal solution and therefore overcome most of the design barriers that prevent wearable sensor systems from being used in normal clinical practice.

1. Introduction

Wearable Monitoring Systems (WMS) refer to the miniaturised ICT systems that are embedded in user's clothing and are devised to collect and transmit biomedical signals seamlessly and unobtrusively. The adoption of such systems is expected to grow significantly in the coming years due to the recent advances on electronics, new long term physiological monitoring requirements, and healthcare costs reduction needs. A myriad of such systems has already been described in the scientific literature [1, 2], addressing a disparity of pathologies and clinical frameworks. Nevertheless, the design of suitable and usable WMS remains a challenge due to the number of technical and medical issues they are still faced with [3, 4]:

(i) Size, weight, cost, and power consumption.

(ii) Data availability and security, interoperability, privacy, dependability, and connectivity.

(iii) User comfort, wearability, man-machine interaction, safety, user, and healthcare convenience [5].

Among all the possible physiological monitoring applications of WMS, detection and management of cardiac conditions during daily activities are probably the most important and most studied one. Cardiovascular disease risk assessment requires continuous long term monitoring for accurate diagnosis and treatment management. WMS very well suit these needs, and with heart diseases being among the most widespread, yet preventable and costly health problems in the developed countries, investment in WMS will pay off. Heart failure is one of the leading causes of mortality, disability, hospitalization, and overall health care-related costs [6].

However, the advent of ubiquitous physiological WMS for cardiac pathologies is also constrained by the issues stated above. There are a number of conflicting and competing WMS features, and in order to achieve a successful clinical introduction and operation of these systems, an efficient management and optimisation scheme of the interactions among these conflicting features has to be achieved.

This paper introduces a methodological approach for selecting the most appropriate WMS configuration for cardiac activity monitoring. It is based on a multiobjective framework, using regression models to define the cost functions from the design variable space: skin contact, sensor location, sensor rotation, correlation, and comfort. The objective functions chosen were functionality and wearability, as a trade-off between computational cost and performance.

Several works have been developed recently, aiming at addressing the automated WMS design. Thus, the construction of WSM prototypes is carried out in [7–11], using a set of design variables previously fixed. Besides, the set of adopted variables in some cases is given through very particular models, which may restrain their generalisation to different applications. However, their major limitation is that they do not carry out an optimisation stage to confront conflicting design architectures to deal better with heterogeneous systems consisting of different sorts of components or with communication aspects. On the other hand, two works make significant efforts to automatize the optimised design of WSM applications. In [12, 13], the focus is on codification of the specific wearable design criteria (including functionality and wearability) into formal metrics to be further included within an appropriate optimisation framework. The biggest restriction they may face in real-world applications is the linear fitting of cost functions they assume. As a matter of fact, the interaction between so wide-nature variables of design barely can be related as linear.

Methods for building the optimisation objectives from the design variable space can be divided into two categories: analytic and heuristic. The analytic methods are grounded in mathematical formalisms to represent knowledge concerning the underlying physical processes as described in [14–17]. The analytical formulation provides a more accurate picture of the relationships between constraints and multiobjective statements, but it can only handle a very few design variables due to the complexity of the physical processes involved. Furthermore, they exhibit poor scalability, making the addition of new variables difficult.

On the contrary, the knowledge-based methods rely on informal models, given as a set of intuitive rules, and are particularly valuable when there is not enough quantitative information. Heuristic methods have been used for assembling cost functions from variable spaces in applications from different backgrounds. For example, a single cost optimisation scheme is presented in [18] as a sum of the cost functions computed by multicolony ant algorithms for beams and columns in reinforced concrete buildings. In [19], a game tree search algorithm and Heuristic Route Planning are proposed for a multiobjective discretised control problem. In [20], a branch-and-bound based conflict driven clause learning algorithm is used for optimally solving minimum cost problems. In [21], a fast human-in-the-loop path planning strategy is proposed based on a cloud model using fuzzy and probability principles.

This paper uses a heuristic approach that better matches the needs and available know-how in the cardiac WMS realm. We studied two multivariate regression models (linear and nonlinear) to encompass several input observations and more than one output variable (real-valued and categorical). We employed Feedforward Neural Networks (FNNs) for nonlinear regression modelling due to their strong ability to approximate complex mappings directly from the input samples [22]. There was more than one global optimisation design goal (objective function), each of which may have an uncooperative self-optimal decision. To cope with this issue, the solution of the multiobjective optimisation (MOOP) setup proposed is represented by a set of efficient points (Pareto optimal set), which included all decision vectors in which the corresponding objective vector could not be further improved in any dimension without degradation in another one [23]. However, the complexity of MOOP tasks turns out to be more significant as the size of the problem grows, namely, as the number of objective functions and dimension of the search space increase [24]. In the case of WMS, the MOOP-based solutions rely on empirical procedures (trial and error guessing) and experience of designers. These tasks are too demanding to be performed manually, but too complex to be carried out automatically [25]. Therefore, we propose a more efficient and scalable MOOP tool that can be of great benefit in cardiac WMS, especially when the optimisation tasks become more complex. In order to compute a solution for the MOOP, a genetic algorithm (GA) was used. For validation purposes, we carried out a set of experiments, using the proposed design variables, on 12 healthy volunteers aged between 20 and 30 years. The results show that the nonlinear regression modeling of the cost functions provides a better fitting, allowing the WSM layout design to reach an optimal trade-off between the two objective functions analysed: functionality and wearability. Therefore, our proposed methodology extends existing basic design approaches to their automated version that may be performed as a further stage to improve this class of approaches. Besides, our approach allows experimentally modeling the cost function space in a linear or nonlinear way, to fulfill more realistic conditions of design.

The remainder of this paper is organised as follows. In Section 2, we describe the set of candidate design variables, the objective function definition process based on regression modelling, and the MOOP framework employed. In Section 3, we describe a realistic study case and detail the results on performance evaluation of the WMS. Next, Section 4 provides a brief discussion about the implications of the experimental results on the WMS design. Finally, the paper ends with some concluding remarks in Section 5.

2. Methods

Several works have addressed the definition of an adequate MOOP framework for WMS design [12, 26]. A comprehensive review of MOOP evolutionary algorithms is given in

Table 1: List of commonly used conflicting goals (objective functions) for WMS design and their description.

Objective function	Description
Functionality [7–10, 12, 28–32]	Specific technical functions in an efficient and friendly manner
Wearability [7–12, 28–30, 33–36]	Ergonomics, obtrusiveness, comfort, look, fashionability, weight, size, and correspondence between shape and placement on the body
Resources cost [7, 8, 30, 31, 34]	Determined by the technology state of the art, cost, compatibility, and other strategic concerns
Power consumption [8, 9, 12, 13, 16, 30–32, 35]	Long term use, energy harvesting, and power saving modes
Recognition [13, 30, 33]	Classification accuracy and pattern recognition performance
Usability [7, 8, 30, 32, 34]	User experience
Maintainability [8, 31, 34]	Launderable, dimensional stability, software upgradable, and rechargeable battery
Durability [8, 30, 34]	Flexural endurance, mechanical tear, tensile, shear, and burst strength and resistance to abrasion, corrosion, heat, and electricity
Desirability [29]	Social factors, continuous use, pre- and postadoption user behaviour, and decision drivers

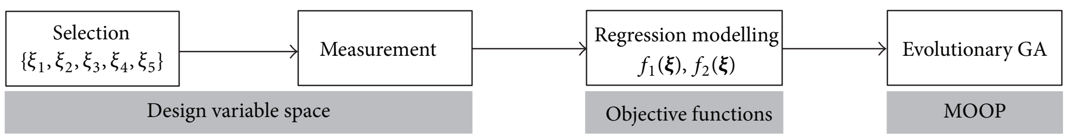

Figure 1: General framework for the proposed WMS optimisation. From the design variable space, a subset is selected and quantified. Then, applying regression modelling, the objective functions are defined. Finally, an optimal solution is found using evolutionary algorithms.

[27] for solving various complex problems. The commonly recommended stages are (Figure 1) as follows:

(i) Formalisation of the design constraints based on the hardware resources, the architecture device models, and the user's context and identification of critical variables that include selection and measurement of the most influencing functions and variables during the WMS design process.

(ii) Formulation of the optimisation goals in quantitative terms: multiobjective representation.

(iii) MOOP using any of the many evolutionary algorithms that have been already proposed in the scientific literature.

The first two concurring stages relate to defining the available objective functions that must be modelled by means of a feasible design variable set. This definition exerts the greatest influence on the MOOP task performance, and, therefore, it is of paramount importance to achieve an effective WMS layout. The objective functions must include the domain plurality of the modelling variables (quantitative and categorical), and the decision variable domains must satisfy the assumed set of constraints. Although the individual modelling of subsystems may be more suitable in some cases, the overall WSM layout relies on the efficient integration of a larger amount of decision variables. The following subsections describe the model implementation proposed for an efficient cardiac WSM scheme.

2.1. Objective Functions. A detailed list of the objective functions and their meaning that have been widely recommended for the design of WMS is shown in Table 1. This information has been obtained after an extensive review of the related scientific literature.

Although the number of WSM objective functions suggested in literature is large enough, each one is usually modeled employing its own set of design variables, making the incorporation of more extensive design spaces very expensive. For the sake of a reasonable cost implementation, we validate our proposed approach using just two available cost functions f: functionality (termed f_1) and wearability (f_2). Based on the same ground, many studies have been carried out mainly using both design variables as seen in Table 1. Representative examples of their use for wearable sensor systems include [8–10, 12, 13, 28, 29, 37]. It is worth noting that the proposed approach of multiobjective design devoted to wearable sensor systems for electrocardiogram monitoring is so flexible that it can be extended to other feasible design spaces without substantial changes.

The variable subset is selected as to include each measuring principle for WMS design: hardware sensors, data processing, and communications and interaction with the user. Therefore, the variable subset $\boldsymbol{\xi}$ is chosen based on the expected influence on the objective functions $f_1(\boldsymbol{\xi})$ and $f_2(\boldsymbol{\xi})$. In the particular case of ECG monitoring, the constraints reflecting where sensors can gather useful information about the human body and the constraints of wearability should be strongly considered [37]. Moreover, the following variables have been reported as having a substantial influence on the ECG measurement: sensor location [12, 30, 33, 38], the electrode-skin contact [30, 38, 39], and signal quality [13, 28, 30]. Despite this reported importance, a close relationship

Table 2: List of the frequently reported variables relating to each measuring principle for WMS design.

Hardware	Processing	Interaction
Size (volume) [7, 13, 28, 30–35]	Latency [12, 13]	Skin irritation [8]
Weight [7–9, 12, 13, 28, 30, 31, 33–35]	Processing power and computational cost [16, 30, 32]	Comfort, thermal aspects, heat dissipation [8–13, 30, 31, 33]
Electrical resistance [8, 30]	Security and privacy [8, 30, 31]	User Interface [11, 30–32]
Stiffness and flexural endurance [8, 30]	Communication channels, networking [7, 8, 13, 30, 31, 34]	Weather [11, 30]
Fluid repellency [28, 40]	Storage capacity and memory [7, 10]	Need for survival and medical prescriptions [30, 41–43]
Magnetic shielding and radiation concerns [8, 13, 28, 30]	Dynamic voltage scaling techniques and power modes [16, 30]	Aesthetics and form language [9, 12, 13, 30, 33, 35]
Stretchability [8, 30]	Sensor resolution [13, 30]	
Skin contact quality body fit [9, 11, 13, 28, 30, 31, 33, 35, 38]	Sensitivity to changes in R-S interval [30, 39]	
Sensor location and body placement [12, 30, 33, 38]	Correlation and mutual information with reference signals [13, 28, 30]	
Sensor rotation [30]	Sampling rate/sampling frequency [16, 30]	

between them remains an open issue. Therefore, the hardware variables chosen for final design variable set $\boldsymbol{\xi}$ are skin contact (termed ξ_1), sensor location (ξ_2), and sensor rotation (ξ_3). Correlation (ξ_4) is selected from the group of processing variables, as an indicator of the quality of the signal. Finally, comfort (ξ_5) is taken as a measure of human perception (interaction variable).

2.2. Design Variables. A detailed list of the most frequently used WSM design variables is shown in Table 2. They are grouped according to their role in the WMS: hardware sensors, data processing and communications, and interaction with the user. As in the previous case, this information has been obtained after an extensive review of the related scientific literature.

It is not advisable to enter all of these variables into the MOOP method for practical reasons. The design variable subset should be selected according to some optimisation criteria [44]. In this work, the variable subset $\boldsymbol{\xi}$ was chosen based on the expected influence on the objective functions $f_1(\boldsymbol{\xi})$ and $f_2(\boldsymbol{\xi})$. According to this criterion, the final design variable set $\boldsymbol{\xi}$ chosen was skin contact (termed ξ_1), sensor location (ξ_2), sensor rotation (ξ_3), correlation (ξ_4), and comfort (ξ_5). The first three variables are related to hardware sensors, the next one relates to processing ability, and the last one relates to interaction.

2.3. Objective Functions Regression Modelling. Regression modelling is proposed as the method to quantify the relationship between the design variable set and the objective functions of the WMS, $\mathbf{f}(\boldsymbol{\xi})$. We propose two modelling schemes based on linear and nonlinear techniques in order to compare their performance. All the regression models are multivariate, comprising several input observations and more than one outcome variable. In addition, they can handle real-valued and categorical variables.

2.3.1. Linear Regression Modelling. The objective of this modelling is to predict a response function f_n from the design explanatory set $\boldsymbol{\xi}$ by finding a particular linear relationship $f_n = \phi(\boldsymbol{\xi} \mid \boldsymbol{\theta}_n)$ that should correlate maximally with f_n (usually, by minimizing the sum of squared deviations), where $\phi(\cdot)$ is a scalar-valued estimator and $\boldsymbol{\theta}_n$ is a vector holding the corresponding model parameters. In particular, we assume the explanatory vector consisting of $M = J + P$ variables, with J real variables $\xi_j \in \mathbb{R}$, $j = 1, \ldots, J$ and P categorical variables $\xi_p \in \{1, \ldots, Q_p\}$, $p = 1, \ldots, P$, where Q_p is the number of categories on the pth variable. Thus, the following linear regression model is considered [45]:

$$\mathbf{f}(\boldsymbol{\xi}) = \boldsymbol{\eta} + \sum_{j=1}^{J} \boldsymbol{\alpha}_j \xi_j + \sum_{p,q=1}^{P,Q_p-1} \boldsymbol{\beta}_p^q \delta_p^q + \sum_{j,p,q=1}^{J,P,Q_p-1} \boldsymbol{\gamma}_{jp}^q \xi_j \delta_p^q, \quad (1)$$

where $\delta_p^q = \delta(\xi_p - q)$ is an indicator (qualitative) variable, $\delta(\cdot)$ is the Dirac delta function, $\boldsymbol{\alpha}_j \in \mathbb{R}$ is the vector of the coefficients associated with real variables J to the output function f_n, $\boldsymbol{\beta}_p^q \in \mathbb{R}$ are the coefficients related to the qth category of p variable, $\boldsymbol{\gamma}_{jp}^q \in \mathbb{R}$ is the vector of the interaction coefficients between J real variables and P categorical variables, and $\boldsymbol{\eta}_n \in \mathbb{R}$ is a constant vector.

2.3.2. Nonlinear Regression Modelling. In this case, heuristic learning algorithms identify multiple levels of representation (explanatory factors), with higher-level features representing more abstract aspects of the data. Specifically, we use a FNN that is a function $\phi : \mathbb{R}^M \to \mathbb{R}^N$ that maps nonlinearly the objectives into the conflicting functions as follows [46]:

$$\mathbf{f}(\boldsymbol{\xi}) = \left(\mathbf{b}^U + \mathbf{W}^U \mathbf{z}^{U-1}\right), \quad (2a)$$

$$\mathbf{z}^u = s\left(\mathbf{b}^u + \mathbf{W}^u \mathbf{z}^{u-1}\right), \quad (2b)$$

where $\mathbf{b}^u \in \mathbb{R}^{1\times M_{\mathbf{z}^u}}$ is the bias vector, $M_{\mathbf{z}^u}$ is the number of units in the u layer, $u = 0,\dots,U$ (U being the network depth), $\mathbf{W}^u \in \mathbb{R}^{M\times M_{\mathbf{z}^u}}$ is the weighting matrix connecting the hidden layer u with the hidden layer $u-1$, $\mathbf{z}^u \in \mathbb{R}^{M_{\mathbf{z}^u}}$ holds the hidden layers, and s is an activation function that typically is assumed as the tanh or the logistic *sigmoid* function. Here, we assume $\mathbf{z}^0 = \boldsymbol{\xi}$ as the input training set.

2.4. MOOP Solution. The general constrained MOOP is formally stated as follows [47]:

$$\underset{\forall\boldsymbol{\xi}\in\mathcal{X}}{\text{minimize}} \quad \mathbf{f}(\boldsymbol{\xi}) = \left[f_1(\boldsymbol{\xi}),\dots,f_n(\boldsymbol{\xi}),\dots,f_N(\boldsymbol{\xi})\right]^\top, \quad N \geq 2, \tag{3a}$$

$$\text{subject to} \quad g_k(\boldsymbol{\xi}) \leq 0, \quad k = 1,\dots,K, \tag{3b}$$

$$h_l(\boldsymbol{\xi}) = 0, \quad l = 1,\dots,L, \tag{3c}$$

where $\mathbf{f}(\cdot) \in \mathbb{R}^N$ is a vector of conflicting objective functions (*cost functions*) $f_n(\boldsymbol{\xi}) : \mathbb{R}^M \to \mathbb{R}$ that we want to minimise simultaneously. Each objective function is defined along with $K \in \mathbb{N}$ penalty functions, $\{g_k : \mathbb{R}^M \to \mathbb{R}\}$, and $L \in \mathbb{N}$ equality constraints $\{h_l : \mathbb{R}^M \to \mathbb{R}\}$. $\boldsymbol{\xi} \in \mathbb{R}^M$ is column-vector $\boldsymbol{\xi} = [\xi_1,\dots,\xi_M]^\top$ containing the set of $M \in \mathbb{N}$ design variables, $\xi_m \in \mathbb{R}[\xi_m^{\min}, \xi_m^{\max}]$, also termed *decision variables*.

A solution satisfying a set of $K + L$ given constraints and $2M$ variable bounds constitute the nonempty *feasible variable space* $\mathcal{X} \subset \mathbb{R}^M$, where the optimal vector of decision variables, $\boldsymbol{\xi}^*$, is the point that maximises the vector objective function $\mathbf{f}(\boldsymbol{\xi})$, generating the feasible objective space; that is, $\mathcal{Z} = \{\mathbf{f}(\boldsymbol{\xi}^*) \mid \boldsymbol{\xi}^* \in \mathcal{X}\}$.

The optimising point, $\boldsymbol{\xi}^* \in \mathcal{X}$, is said to be Pareto optimal iff there is not another point, $\boldsymbol{\xi} \in \mathcal{X}$, such that $\mathbf{f}(\boldsymbol{\xi}) \leq \mathbf{f}(\boldsymbol{\xi}^*)$, and $f_n(\boldsymbol{\xi}) \leq f_n(\boldsymbol{\xi}^*)$, for at least one objective function. The Pareto optimum rarely yields a single solution, but rather a set of solutions called Pareto optimal set or nondominated solutions. Therefore, all Pareto optimal points lie on the boundary of the feasible criterion space $\mathcal{Z}$ or in the locus of the tangent points of the objective functions, known as the *Pareto front*.

3. Experiments and Results

3.1. Design Variables Measurement. Measurements related to ξ_1, ξ_2, and ξ_3 were taken for up to 6 or 7 minutes. The subjects had to wear the sensors using each specific configuration under test. Periods of 5-minute rest were included between each test. The maximum duration of the experiments was devised to minimise the possibility of inducing hemodynamic changes (blood flow redistribution) due to wearing compressive garments, as stated in [48]. The number of measurements for each volunteer was 160, with 8 levels of skin contact, 4 body sensor locations, and 4 different rotation angles.

In accordance with earlier reported experimental setups [39, 49], a stepwise application of controlled compression (ξ_1) was carried out ranging from 6 to 16 mmHg by steps of 2 mmHg. The adjustment of the sensor-skin compression

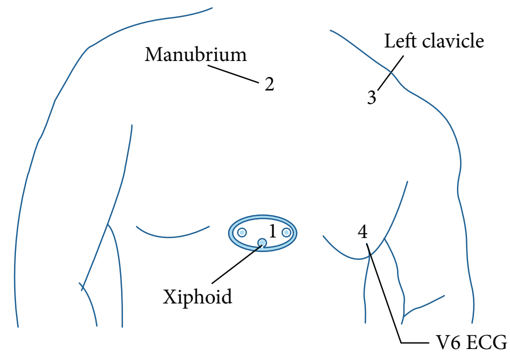

Figure 2: Standard locations for ECG measurements used as one of the categorical variables of the design set, ξ_2.

was performed using a Riester Katch-Kuff manometer. In addition, the measurements were repeated at the four standard chest places (see Figure 2), which are more reliable in terms of skin contact. For every ξ_2, ξ_3 was set to 0, 45, 90, and 135°. For each resulting configuration, the ECG was acquired by a device attached to the pressure cuff and located on a chest strap. The ECG monitor used was the Electrodoctor® recorder, supplied by the company CELBIT LTDA [50].

Experiments were carried out on 12 healthy volunteers (4 females and 8 males), aged between 20 and 35, with weight ranged from 58 Kg to 75 Kg and height between 1,58 m and 1,78 m. Measurements were taken at 2150 meters above sea level. The average temperature was 22°C. The relative humidity was between 60% and 75%.

Measurements related to ξ_4 were based on computing the correlation $\rho \in \mathbb{R}[-1, 1]$ between each recorded ECG signal and a fixed reference pattern [51]. The higher this correlation index, the more accurate the physiological monitoring. As a reference signal, we used records acquired in a resting state within a window of 1 s. In order to account for time shifts between the reference and the test signals, we considered the maximum correlation index obtained with a set of lagged copies of the ECG records for each compression level and the reference patterns. Figure 3(a) shows the results of the computed ξ_4 at every ξ_2 as a function of ξ_1 and for $\xi_3 = 0°$, whereas Figure 3(b) depicts the relationship between ξ_4 and ξ_3, with $\xi_2 = 1$ and as a function of ξ_1 too.

Measurements related to ξ_5, as well as functionality and wearability, were quantified between 0 and 1 [52], with 1 being the highest degree of comfort, functionality, or wearability perceived by the users and 0 the lowest one. A standardized questionnaire was filled in by subjects that were trained to rate each subjective categorical variable. In this way, the score can adapt to different rating scales, such as in [29, 35, 53, 54]. Figure 4 shows additional results for wearability in terms of compression under different year season.

3.2. MOOP Optimisation Results. The MOOP was solved in terms of f_1 and f_2, individually and concurrently. Since multiobjective optimisation problems are usually formulated in terms of minimisation, we minimised the negative of functionality (f_1) and wearability (f_2) instead. The vector

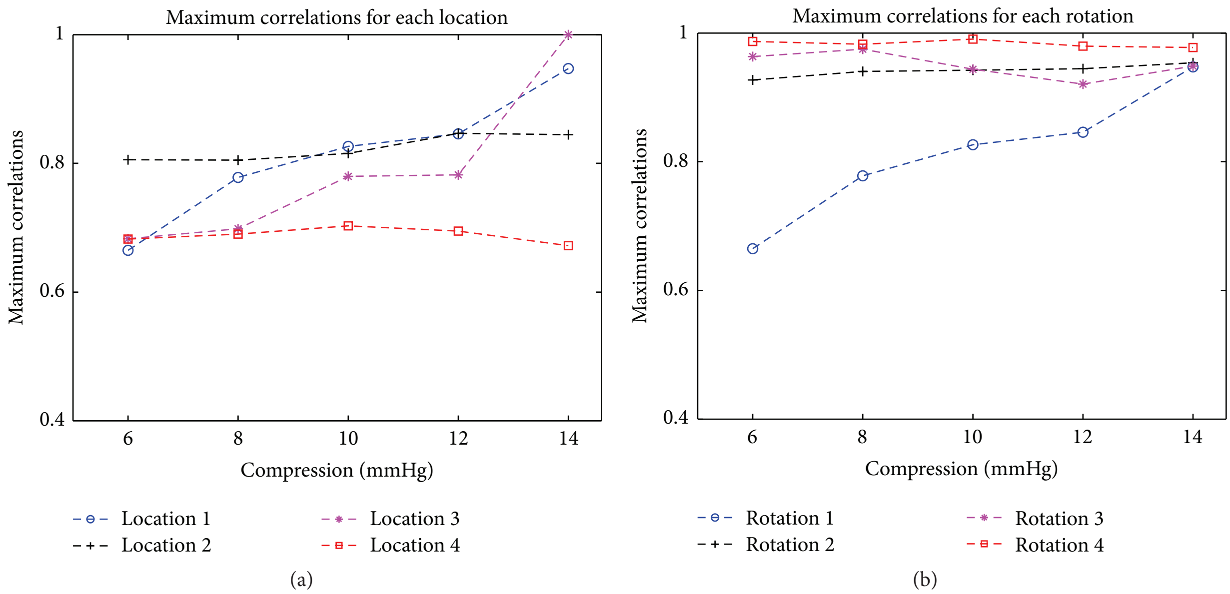

Figure 3: Results for ξ_4 under different input values for ξ_1 and ξ_2.

$-\mathbf{f}$ comprised two objective functions, $-f_i(\xi)$, $\forall i = 1, 2$, where the first one is the lack of functionality, termed dysfunctionality ($-f_1$), and the second one is lack of wearability. As wearables should be unobtrusive, hardly or not perceived by their users [55], the opposite to wearability was termed obtrusivity ($-f_2$). The following equation states the optimisation problem in these minimisation terms, including the specific penalty functions used:

$$\begin{aligned} \underset{\forall \boldsymbol{\xi} \in \mathcal{X}}{\text{minimise}} \quad & -\mathbf{f}(\boldsymbol{\xi}) = \left[-f_1(\boldsymbol{\xi}), -f_2(\boldsymbol{\xi})\right]^{\top}, \\ \text{s.t.} \quad & \text{Compression: } 6\,\text{mmHg} \le \xi_1 \in \mathbb{N} \\ & \le 14\,\text{mmHg} \\ & \text{Location: } 1 \le \xi_2 \in \mathbb{N} \le 4 \\ & \text{Rotation: } 1 \le \xi_3 \in \mathbb{N} \le 4 \\ & \text{Correlation: } 0 \le \xi_4 \in \mathbb{R} \le 1 \\ & \text{Comfort: } 0 \le \xi_5 \in \mathbb{R} \le 1. \end{aligned} \tag{4}$$

Since the decision variables ξ_2 (location) and ξ_3 (rotation) are categorical, the objective function was estimated by using either multiple-linear or nonlinear regressors based on FNN. In order to assess the influence of the outcome design variables, the following three models were studied: a model where the design variable $[\xi_4]$ (correlation) was the only output (MI), a model where $[\xi_5]$ (comfort) was the only output (MII), and a model where $[\xi_4]$ and $[\xi_5]$ were the outputs (MIII). All of these models were considered in linear (denoted as LMx) and nonlinear (NMx) versions.

For implementing and solving the FNN regression defined in (2a), the function *fitting neural network* (`fitnet`) that is an embedded Matlab© procedure was used. The input parameters for this function were 2 hidden layers and

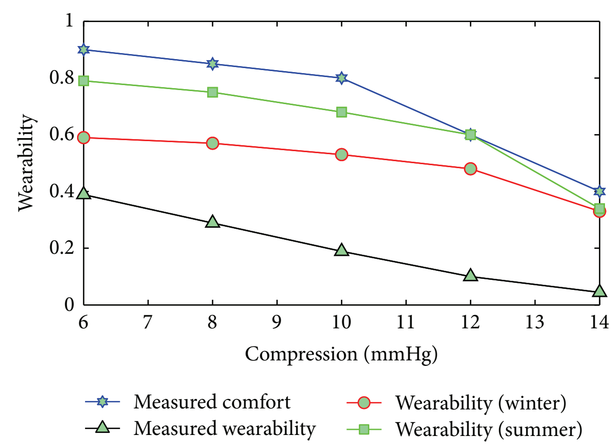

Figure 4: A comparative plot of the wearability and comfort as a function of the compression levels to illustrate the season influence on those parameters.

Bayesian regularisation. This conventional Bayesian regularisation minimises the linear combination of the squared errors r^2 and weights and yields a good generalisation. According to the estimated values of the adjusted r^2, FNN provided a better fitting than the linear regressor. However, the nonlinear procedure demanded a significantly higher computational cost.

In order to solve (3a), we used the GA-based `gamultiobj` solver (Matlab© Global Optimisation Toolbox). This tool applies a controlled elitist genetic algorithm that is a modification of the NSGA-II [56] and includes a nondomination criterion based selection operator to handle multiple objectives. Control parameters of the genetic algorithm were heuristically set as shown in Table 3.

The individual results for $f_1(\boldsymbol{\xi})$ are depicted in Figure 5. The functionality was assessed by the users for the entire

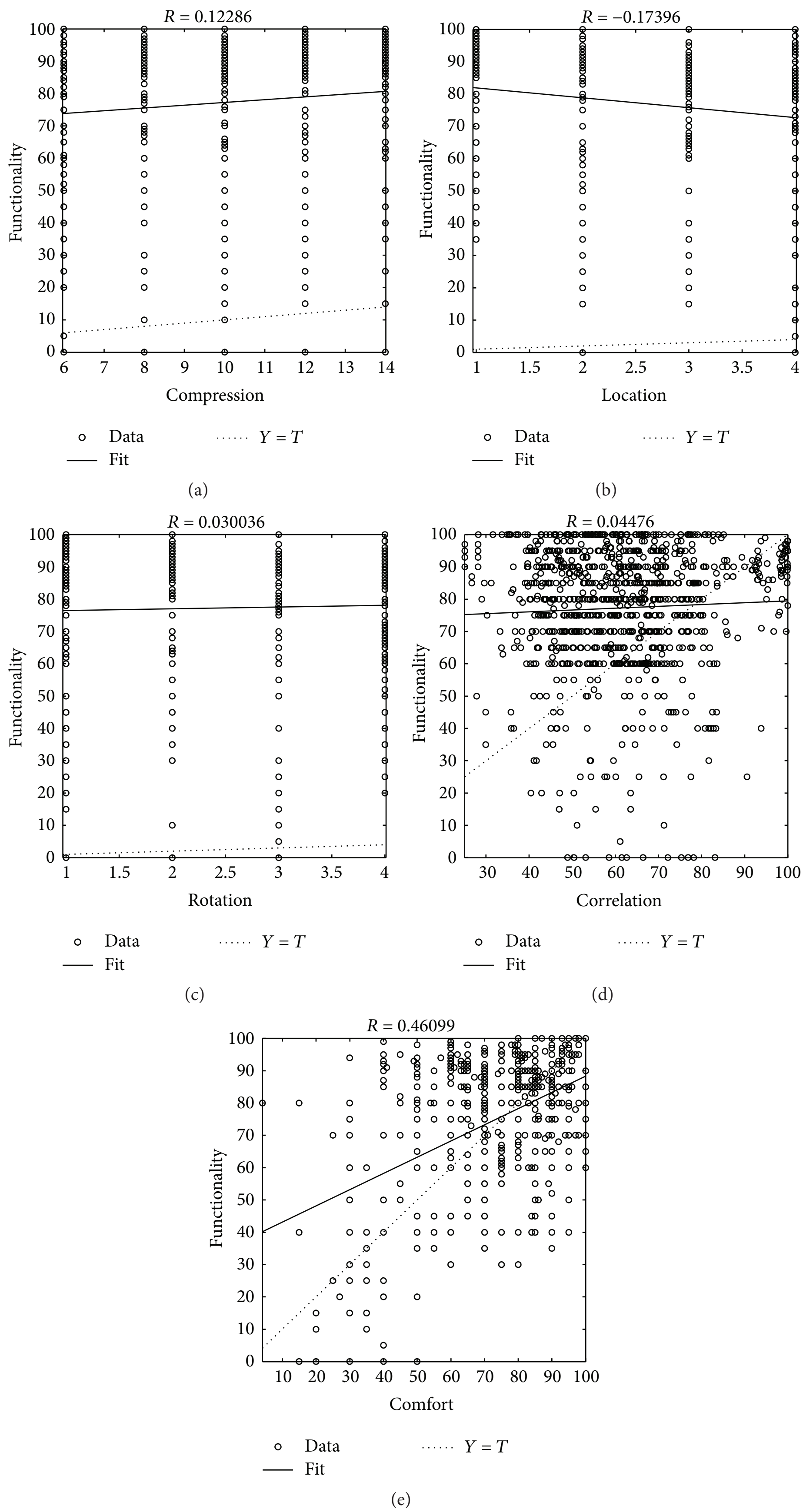

Figure 5: Relationship found between perceived functionality and each design variable. The continuous lines correspond to the linear regression obtained and the circles to data points.

Table 3: Default parameters of the used evolutionary algorithm.

Option	Values	
	Linear with categorical variables	Nonlinear with neural networks
Population size	100 individuals	
Generations	500 iterations	
Crossover fraction	0.8	
Pareto front population	0.35	
Direction in which migration can take place	Previous and next subpopulation	Toward the last subpopulation
Population creation function	Randomly satisfying the constraints	
Selection function	Tournament	
Crossover function	Arithmetic	Intermediate
Mutation function	Uniform	Constraint dependent

Table 4: Model fitness evaluated by the coefficient of determination. Notation [ ] stands for the fixed output variable.

Objective function f_n	Predictors	Coefficient of determination (r)	
		Linear regressor	FNN
Functionality	$\xi_1, \xi_2, \xi_3, [\xi_4]$	0.18767	0.56778
	$\xi_1, \xi_2, \xi_3, [\xi_5]$	0.48498	0.77891
	$\xi_1, \xi_2, \xi_3, [\xi_4], [\xi_5]$	0.48237	0.80344
Wearability	$\xi_1, \xi_2, \xi_3, [\xi_4]$	0.19002	0.59549
	$\xi_1, \xi_2, \xi_3, [\xi_5]$	0.73312	0.88013
	$\xi_1, \xi_2, \xi_3, [\xi_4], [\xi_5]$	0.73611	0.8747

set of different locations and rotations. The linear regression obtained between each variable and functionality is depicted as a continuous line in each subplot ((a)–(d)). Data points are plotted as circles. The same applies to wearability $f_2(\boldsymbol{\xi})$ results, shown in Figure 6.

As a result, the estimated linear models are

$$\begin{aligned}
f_{1\text{LMI}}(\boldsymbol{\xi}) &= 0.3462 + 0.12193\xi_1 - 1.9132\xi_2 \\
&\quad + 0.5284\xi_3 + 0.050696\xi_4, \\
f_{2\text{LMI}}(\boldsymbol{\xi}) &= 0.53225 - 0.11628\xi_1 - 2.0403\xi_2 \\
&\quad - 0.0887\xi_3 - 0.072784\xi_4, \\
f_{1\text{LMII}}(\boldsymbol{\xi}) &= 0.11603 + 0.24059\xi_1 - 1.0113\xi_2 \\
&\quad + 0.5472\xi_3 + 0.48057\xi_5, \\
f_{2\text{LMII}}(\boldsymbol{\xi}) &= 0.12137 + 0.060258\xi_1 - 0.5721\xi_2 \\
&\quad - 0.0866\xi_3 - 0.72607\xi_5, \\
f_{1\text{LMIII}}(\boldsymbol{\xi}) &= 0.082659 + 0.24015\xi_1 - 0.9514\xi_2 \\
&\quad + 0.6208\xi_3 + 0.074268\xi_4 + 0.48436\xi_5, \\
f_{2\text{LMIII}}(\boldsymbol{\xi}) &= 0.13824 + 0.060258\xi_1 - 0.6024\xi_2 \\
&\quad + 0.0494\xi_3 - 0.037543\xi_4 + 0.72416\xi_5.
\end{aligned} \tag{5}$$

Table 4 shows the results estimated for the fitting of both objective functions, f_1 and f_2 (significance level $\alpha = 0.01$). For all three models, a linear regression with categorical covariates in (1) was fitted using the `fitlm` procedure of the statistics Matlab© toolbox. This function uses a least-mean-squares criterion to adjust the regression model parameters. To quantify how well each estimated model fits the data, the coefficient of determination (r) was computed. 73.6% of the wearability (f_2) variance is explained using the linear model with the 5 predictors (LMIII). However, the goodness of fit suggests that the linear approach is not able to adequately predict the functionality. Figure 7 shows the scattered plots generated by each case of regression tested for every output variable. As depicted, FNN yields a more accurate fitting.

Table 5 shows the results for the solution vectors after optimisation for all the models studied, including functionality, wearability, and the global optimisation. Each vector is referenced by a number (# 1 : 18), being the points of maximum functionality enumerated from 1 to 6 (# 1 : 6), maximum wearability from 8 to 12 (# 8 : 12), and the best trade-off from 13 to 18 (# 13 : 18). All of these points are graphically represented in the Pareto fronts of Figure 8. The iterative search strategy yields a set of trade-offs that shape a particular configuration for each objective function model. Every point of the Pareto front denotes one particular configuration of the WSM to be considered.

4. Discussion

Location at $\xi_2 = 3$ yielded the highest ECG quality (Table 5), exhibiting a linear relationship between ρ and ξ_1 (Figure 3(a)). As a consequence, ECG quality improved as the compression increased within the interval ranging from 6

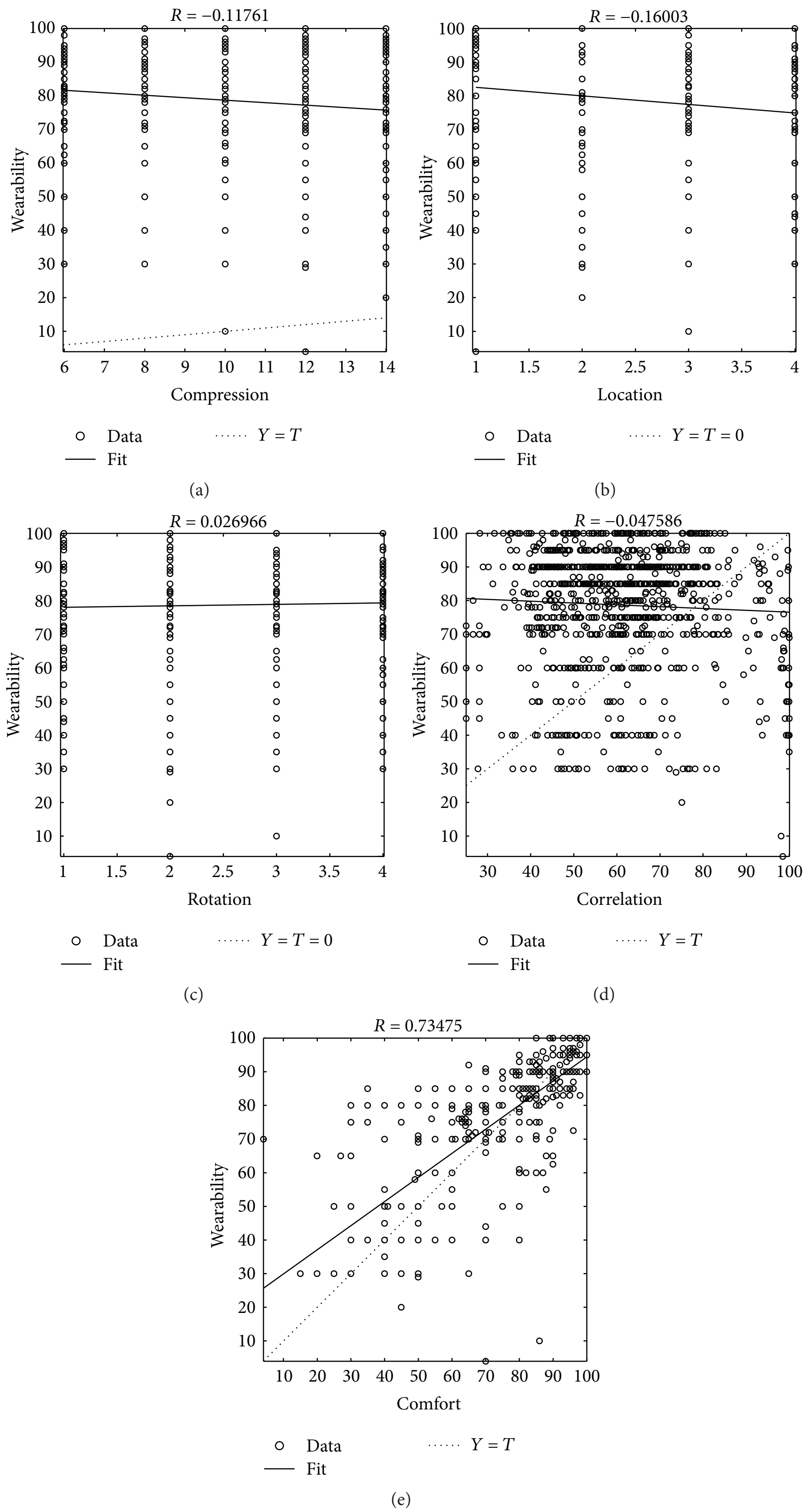

FIGURE 6: Relationship found between perceived wearability and each design variable. The continuous lines correspond to the linear regression obtained and the circles to data points.

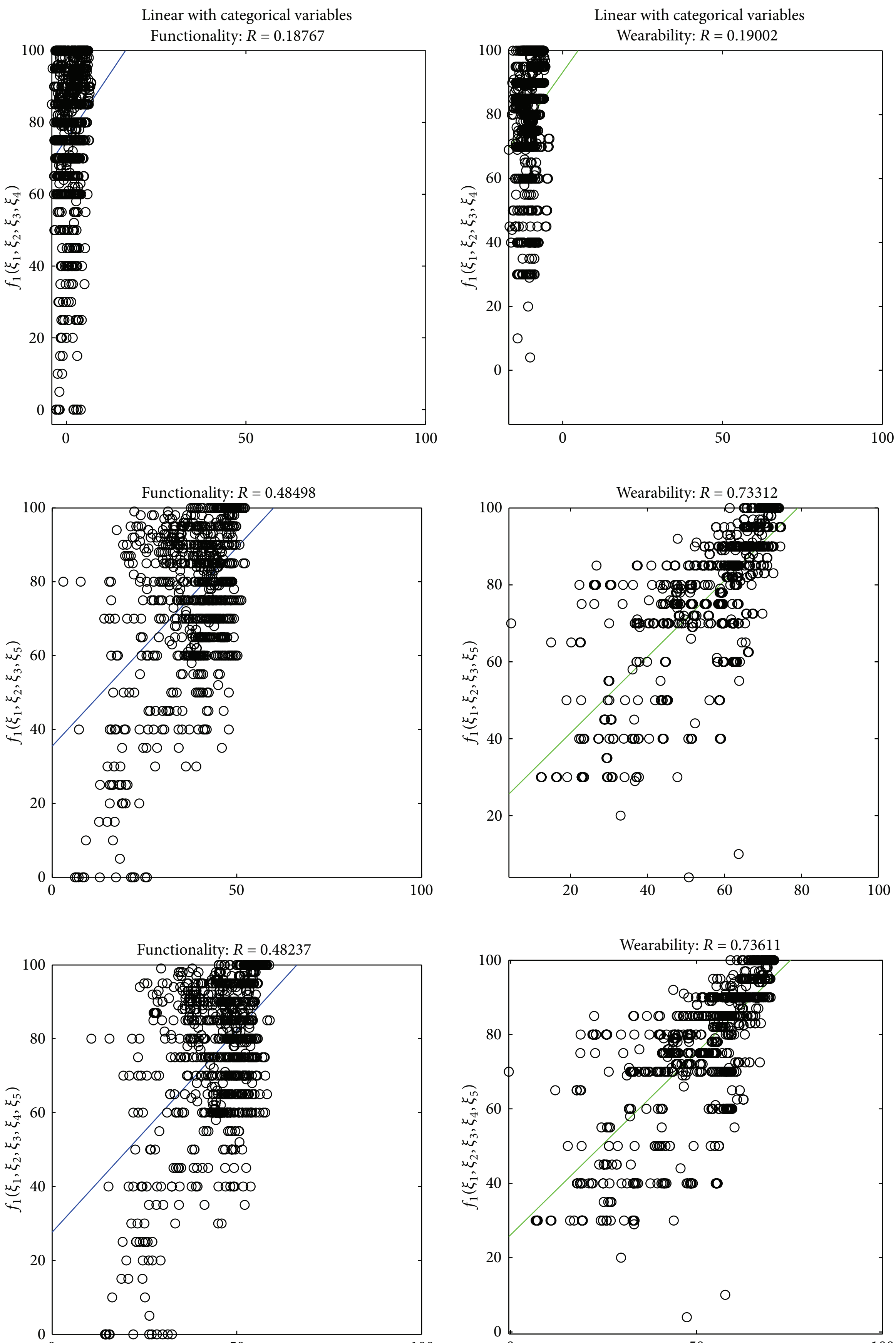

FIGURE 7: Continued.

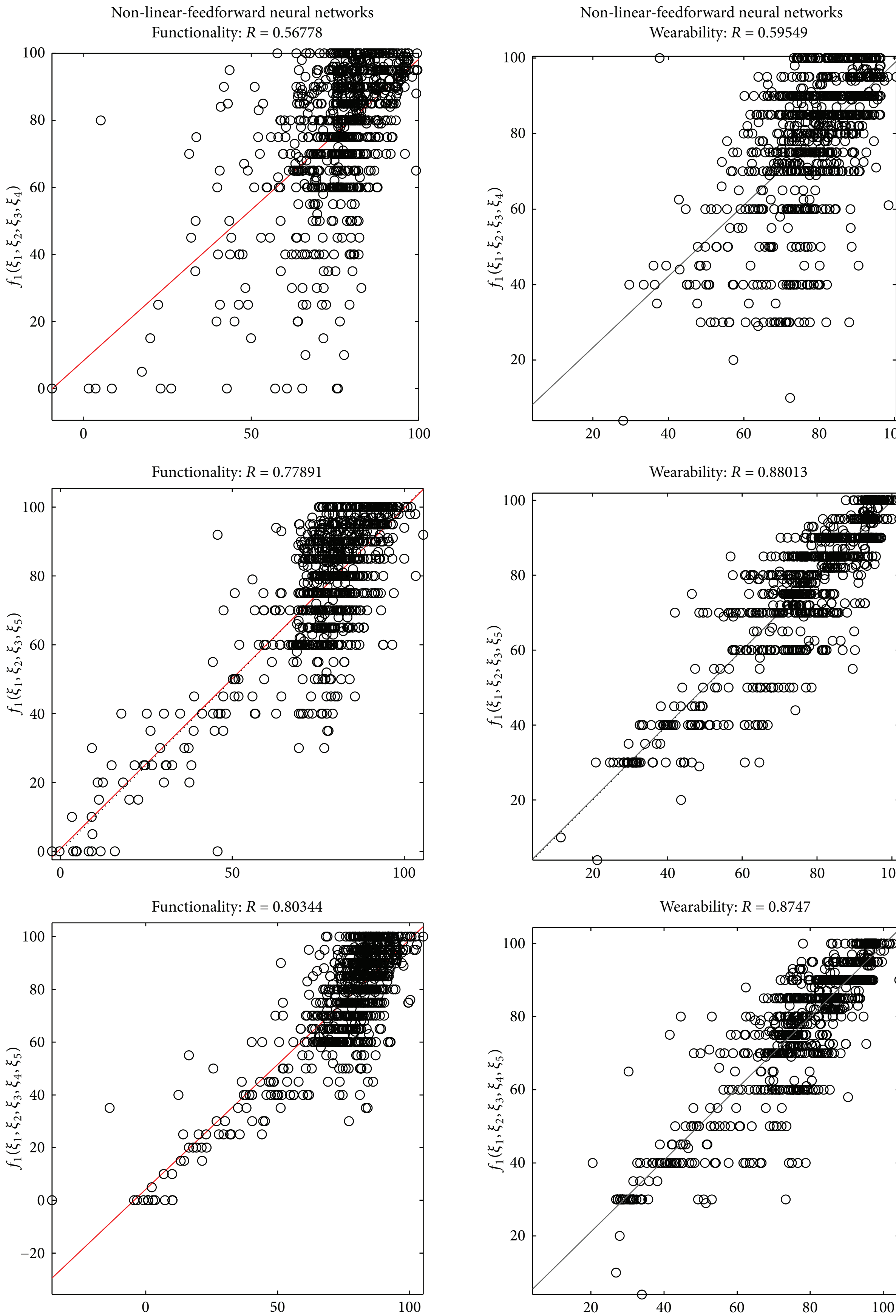

Figure 7: Model fitness computed for each assessed type of regression.

Table 5: Solution vectors after optimisation.

#	Regression model	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	$-f_1$	$-f_2$
				Maximum functionality				
1	LMI	13	2	124	0.5669	—	0.2000	0.1538
2	LMII	14	1	135	—	0.9995	−0.5267	−0.7358
3	LMIII	14	1	133	0.7998	0.9998	−0.5891	−0.7129
4	NMI	13	3	90	0.5125	—	−1.0000	−0.9631
5	*NMII*	*12*	*3*	*100*	—	*0.9460*	***−1.0000***	***−0.9938***
6	NMIII	13	2	65	0.6068	0.7052	−1.0000	−0.7862
				Maximum wearability				
#	Regression model	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	$-f_1$	$-f_2$
7	LMI	13	2	124	0.5669	—	0.2000	0.1538
8	LMII	11	4	135	—	1.0000	−0.4777	−0.7573
9	LMIII	14	1	134	4510	1.0000	−0.5570	−0.7288
10	*NMI*	*13*	*3*	*89*	*0.5076*	—	***−0.9986***	***−1.0000***
11	NMII	12	3	100	—	0.9461	−0.9839	−1.0000
12	NMIII	12	3	98	0.8294	0.9766	−0.4224	−1.0000
				Trade-off				
#	Regression model	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	$-f_1$	$-f_2$
13	LMI	11	1	0	0.4009	—	0.2000	0.1538
14	LMII	14	1	135	—	0.9995	−0.5267	−0.7358
15	LMIII	14	1	133	0.7998	0.9998	−0.5891	−0.7129
16	*NMI*	*13*	*3*	*89*	*0.5076*	—	***−0.9986***	***−1.0000***
17	NMII	12	3	100	—	0.9462	−0.9984	−0.9967
18	NMIII	13	3	98	0.8301	0.9761	−0.9885	−0.9889

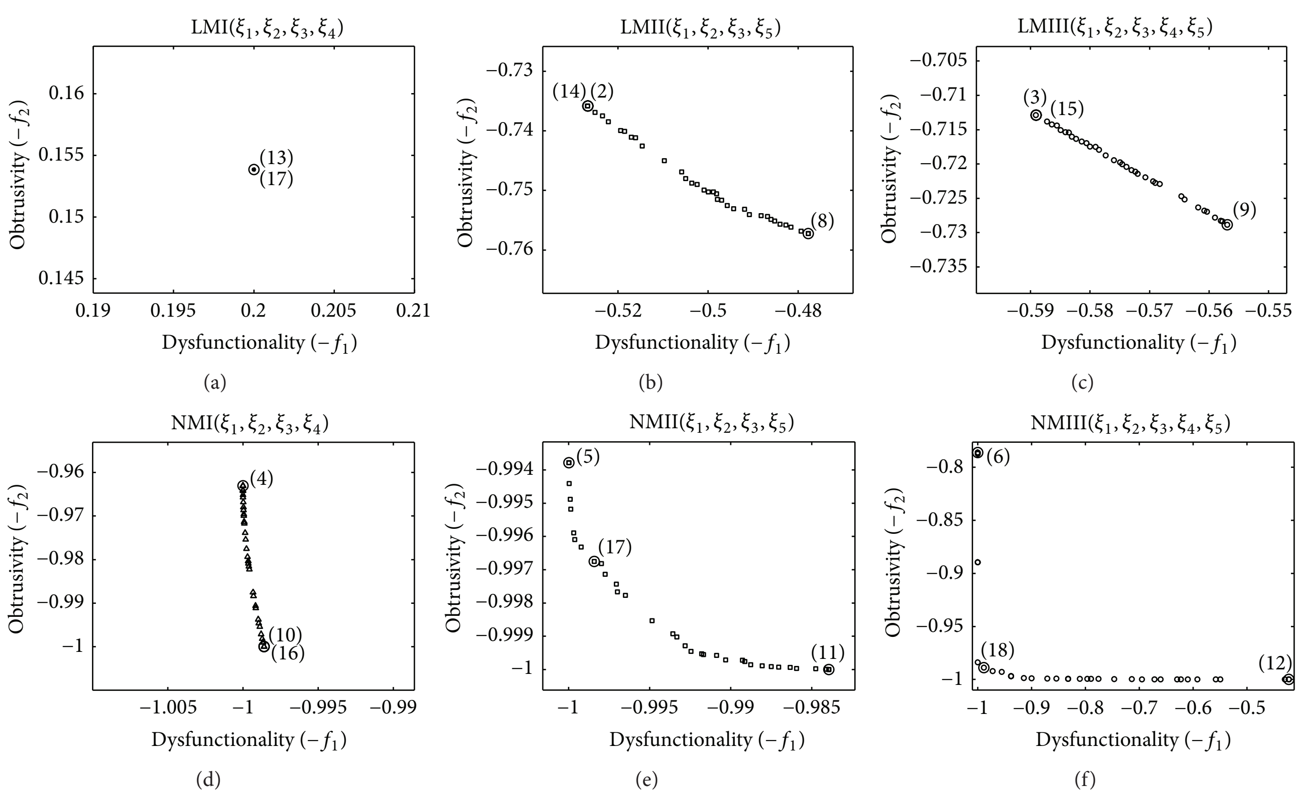

Figure 8: Pareto fronts using linear (a–c) and nonlinear regressions (d–f).

to 14 mmHg. Below 6 mmHg, the sensor adherence is weak, and the ECG may become very noisy. On the other hand, the hemodynamics may be affected when the pressure exceeds 14 mmHg, constraining the chest's expansion seriously. The rest of locations provided a significant lower correlation, mainly for $\xi_1 \leq 12$ mmHg. As for the influence of the rotation on the ECG quality (Figure 3(b)), $\xi_3 = 135^{\circ}$ yielded the highest correlation by far.

Regarding the individual functionality results, the skin contact increased the functionality, as seen in Figure 5(a), but it decreased with the location (Figure 5(b)). The maximum functionality was found for a rotation of $\xi_3 = 0^{\circ}$ (Figure 5(c)). The relationship between the estimated functionality and the correlation index or the comfort was more scattered (Figures 5(d) and 5(e)).

Wearability decreased as skin contact pressure rose (Figure 6(a)). This finding is in accordance with similar results, as those discussed in [57]. This relationship can vary depending on the season of the year [11]. According to the results shown in Figure 6(e), wearability and comfort exhibit a clear direct relationship. The rest of variables seem to have a negligible influence on wearability.

The numerical solutions listed in Table 5 and graphically depicted using Pareto fronts in Figure 8 will be discussed separately next. For the maximum functionality (f_1), the analysis of the solutions # 1 : 3, # 7 : 9, and # 13 : 15 suggests that linear regression models are inadequate to optimise f_1. Nonetheless, the inclusion of all five variables simultaneously (LMIII) increases the level of wearability (f_2) as seen in # 3. A detailed analysis of solutions # 4 : 6 can conclude that the functionality is more strongly related to the quality of the data acquisition (ξ_4), although the maximum wearability is achieved when this variable is not included (NMII). In all of these cases, however, an acceptable level of wearability is achieved ($f_2 > 0.68$).

In the case of wearability, all solutions # 10 : 12 achieve the maximal values. However, globally, the solution # 10 is optimal in this case.

The solution to be selected for the WSM design should meet the best trade-off between both objective functions. Among the linear modelled solutions (# 13 : 15), the point including all five design variables (# 15) yields the best one for this set. However, the FNN-based solution # 16 further minimises the Euclidean norm and reaches the overall best trade-off. This solution predicts a functionality ($f_1 = 0.9986$) and wearability ($f_2 = 1.0000$) with the following input variables: compression $\xi_1 = 13$ mmHg, sensor location $\xi_2 = 3$, and rotation $\xi_3 = 89^{\circ}$. Nevertheless, solution # 16 implies the exclusion of the comfort variable (ξ_5) from the objective function modelling.

5. Conclusion

WMS will soon become standard practice in the physiological monitoring realm. However, there still exist a number of open design issues that can pose a real barrier to their adoption. WMS are governed by a set of antagonistic variables that are difficult to optimise in order to achieve the expected performance.

This paper addresses this problem for the specific case of cardiac monitoring using WMS. We propose a multiobjective WMS design scheme for electrocardiogram recording. The MOOP framework described includes a set of design variables that must meet the requirements of the objective functions selected, enabling the optimisation of the WSM design in the context of ambulatory cardiac assessment.

Although a number of cost functions have been proposed for the design of healthcare devices (Table 1), computationally expensive and very time-consuming criteria were not included in the present study for practical reasons. The design space recommended comprises only two objective functions, functionality and wearability, and a selected subset of five variables (see Table 2), skin contact, sensor location, sensor rotation, correlation, and comfort. The first three variables (hardware) were fixed (input variables), and the latter two were measured (outcome variables).

The heuristic approach was based on a regression analysis. Both linear (multiple-linear regression model) and nonlinear regressions (FNN) are studied, and categorical variables are involved. The linear fit accounted for a moderate-low variance related to each objective function. FNN-based nonlinear regression provided a better fitting than the linear regressor, but at the expense of a higher computational cost.

The estimated Pareto front depicted the best trade-off between functionality (features technical functions in an efficient and friendly manner) and wearability (ergonomics and fashionability issues). A nonlinear modelling should be used to optimise the objective functions since they reflect the required penalty functions. Although nonlinear regressors demand more computational resources, their goodness of fit justifies their use.

There was no clear relationship between the correlation variable and each objective function (Figures 5 and 6), especially in the case of wearability, whereas the relationship between the comfort variable and functionality is inverse and proportional for comfort wearability. As a result, the best setup for functionality was compression 12 mmHg, sensor located at location 3, and sensor rotation 100°. The best setup for wearability was compression 13 mmHg, sensor location 3, and rotation $\xi_3 = 89^{\circ}$.

The use of a MOOP framework is a powerful tool for the design of cardiac monitoring systems since it may interplay cost functions with very conflicting goals. A MOOP framework was used to address the estimation of the regression models to reflect penalty functions for wearability and functionality simultaneously. The Pareto front, computed using genetic algorithms, showed that the optimal solution excludes the correlation as a design variable. This conclusion is more evident for the FNN regression models as seen in Table 5. Therefore, the best setup in terms of trade-off between both objective functions for the WSM design was compression $\xi_1 = 13$ mmHg, sensor position at left clavicle (location 3), and rotation $\xi_3 = 89^{\circ}$.

Additional work in the WMS realm should be devoted to exploring more strategies of Pareto front computation for constrained objective function optimisation. The authors plan to extend the experimental setup to include other important cost functions, like power consumption (short battery life) and usability (lack of user acceptability, healthcare feedback, and imposed limitations on patients) that have been found to be the main drivers for acceptance of ECG monitoring systems [58].

Competing Interests

The authors declare that there are no competing interests regarding the publication of this paper.

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References

[1] S. Ha, C. Kim, Y. M. Chi et al., "Integrated circuits and electrode interfaces for noninvasive physiological monitoring," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 5, pp. 1522–1537, 2014.

[2] Y.-L. Zheng, X.-R. Ding, C. C. Y. Poon et al., "Unobtrusive sensing and wearable devices for health informatics," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 5, pp. 1538–1554, 2014.

[3] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, vol. 40, no. 1, pp. 1–12, 2010.

[4] J. S. Lee, J. Heo, W. K. Lee, Y. G. Lim, Y. H. Kim, and K. S. Park, "Flexible capacitive electrodes for minimizing motion artifacts in ambulatory electrocardiograms," *Sensors*, vol. 14, no. 8, pp. 14732–14743, 2014.

[5] M. Chan, D. Estève, C. Escriba, and E. Campo, "A review of smart homes-Present state and future challenges," *Computer Methods and Programs in Biomedicine*, vol. 91, no. 1, pp. 55–81, 2008.

[6] J. E. M. H. van Bronswijk, "Active ageing: a policy framework—WHO's ageing and life course program; 2002, by the World Health Organisation," *Gerontechnology*, vol. 2, no. 3, pp. 275–276, 2003.

[7] T. Kiryu, T. Moriya, and Y. Mizuno, "Design of wearable units for personal fitting process in wellness environment," in *Proceedings of the IEEE EMBS Asian-Pacific Conference on Biomedical Engineering (APBME '03)*, pp. 42–43, Kyoto, Japan, October 2003.

[8] S. Park and S. Jayaraman, "Enhancing the quality of life through wearable technology," *IEEE Engineering in Medicine and Biology Magazine*, vol. 22, no. 3, pp. 41–48, 2003.

[9] F. Gemperle, C. Kasabach, J. Stivoric, M. Bauer, and R. Martin, "Design for wearability," in *Proceedings of the Second International Symposium on Wearable Computers*, Digest of Papers, pp. 116–122, Pittsburgh, Pa, USA, October 1998.

[10] O. Amft, M. Lauffer, S. Ossevoort, F. Macaluso, P. Lukowicz, and G. Tröster, "Design of the QBIC wearable computing platform," in *Proceedings of the 15th IEEE International Conference on Applications-Specific Systems, Architectures and Processors*, pp. 398–410, Galveston, Tex, USA, September 2004.

[11] S. Raj and S. Sreenivasan, "Total wear comfort index as an objective parameter for characterization of overall wearability of cotton fabrics," *Journal of Engineered Fibers and Fabrics*, vol. 4, no. 4, pp. 29–41, 2009.

[12] U. Anliker, J. Beutel, M. Dyer et al., "A systematic approach to the design of distributed wearable systems," *IEEE Transactions on Computers*, vol. 53, no. 8, pp. 1017–1033, 2004.

[13] U. Anliker, H. Junker, P. Lukowicz, and G. Tröster, "Design methodology for context-aware wearable sensor systems," in *Pervasive Computing*, H. W. Gellersen, R. Want, and A. Schmidt, Eds., vol. 3468 of *Lecture Notes in Computer Science*, pp. 220–236, Springer, Berlin, Germany, 2005.

[14] A. Razzaque, C. S. Hong, and S. Lee, "Data-centric multiobjective QoS-aware routing protocol for body sensor networks," *Sensors*, vol. 11, no. 1, pp. 917–937, 2011.

[15] F. V. C. Martins, E. G. Carrano, E. F. Wanner, R. H. C. Takahashi, and G. R. Mateus, "A hybrid multiobjective evolutionary approach for improving the performance of wireless sensor networks," *IEEE Sensors Journal*, vol. 11, no. 3, pp. 545–554, 2011.

[16] I. Beretta, F. Rincon, N. Khaled et al., "Model-based design for wireless body sensor network nodes," in *Proceedings of the 13th Latin American Test Workshop (LATW '12)*, pp. 1–6, IEEE, Quito, Ecuador, April 2012.

[17] T. Rault, A. Bouabdallah, and Y. Challal, "Energy efficiency in wireless sensor networks: a top-down survey," *Computer Networks*, vol. 67, pp. 104–122, 2014.

[18] P. Sharafi, M. N. S. Hadi, and L. H. Teh, "Heuristic approach for optimum cost and layout design of 3D reinforced concrete frames," *Journal of Structural Engineering*, vol. 138, no. 7, pp. 853–863, 2012.

[19] E. J. Powley, D. Whitehouse, and P. I. Cowling, "Monte Carlo Tree Search with macro-actions and heuristic route planning for the Multiobjective Physical Travelling Salesman Problem," in *Proceedings of the IEEE Conference on Computational Intelligence in Games (CIG '13)*, pp. 1–8, Niagara Falls, Canada, August 2013.

[20] V. D'Silva, L. Haller, and D. Kroening, "Abstract conflict driven learning," in *Proceedings of the 40th Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (POPL '13)*, pp. 143–154, ACM, Rome, Italy, January 2013.

[21] X. Sun, C. Cai, and X. Shen, "A new cloud model based human-machine cooperative path planning method," *Journal of Intelligent and Robotic Systems: Theory & Applications*, vol. 79, no. 1, pp. 3–19, 2015.

[22] S. Wang, F.-L. Chung, J. Wu, and J. Wang, "Least learning machine and its experimental studies on regression capability," *Applied Soft Computing Journal*, vol. 21, pp. 677–684, 2014.

[23] E. Zitzler and L. Thiele, "Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach," *IEEE Transactions on Evolutionary Computation*, vol. 3, no. 4, pp. 257–271, 1999.

[24] R. R. Kurada, K. K. Pavan, and A. V. D. Rao, "A preliminary survey on optimized multiobjective metaheuristic methods for data clustering using evolutionary approaches," *International Journal of Computer Science & Information Technology*, vol. 5, no. 5, pp. 57–77, 2013.

[25] R. Khusainov, D. Azzi, I. E. Achumba, and S. D. Bersch, "Real-time human ambulation, activity, and physiological monitoring: taxonomy of issues, techniques, applications, challenges and limitations," *Sensors*, vol. 13, no. 10, pp. 12852–12902, 2013.

[26] W.-T. Sung and Y.-C. Chiang, "Improved particle swarm optimization algorithm for android medical care IOT using

modified parameters," *Journal of Medical Systems*, vol. 36, no. 6, pp. 3755–3763, 2012.

[27] C. Von Lücken, B. Barán, and C. Brizuela, "A survey on multi-objective evolutionary algorithms for many-objective problems," *Computational Optimization and Applications*, vol. 58, no. 3, pp. 707–756, 2014.

[28] F. J. Martinez-Tabares, J. A. Jaramillo-Garzon, and G. Castellanos-Dominguez, "Multiobjective optimization-based design of wearable electrocardiogram monitoring systems," in *Proceedings of the 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC '14)*, pp. 3029–3032, IEEE, Chicago, Ill, USA, August 2014.

[29] K. Bodine and F. Gemperle, "Effects of functionality on perceived comfort of wearables," in *Proceedings of the 7th IEEE International Symposium on Wearable Computers (ISWC '03)*, pp. 57–60, White Plains, NY, USA, October 2003.

[30] A. Bonfiglio and D. De Rossi, *Wearable Monitoring Systems*, Springer, New York, NY, USA, 2010.

[31] T. Starner, "The challenges of wearable computing: part 1," *IEEE Micro*, vol. 21, no. 4, pp. 44–52, 2001.

[32] C. Burgy, *An interaction constraints model for mobile and wearable computer-aided engineering systems in industrial applications [Ph.D. thesis]*, AAI3045237, Carnegie Mellon University, Pittsburgh, Pa, USA, 2002.

[33] K. Murao, H. Mogari, T. Terada, and M. Tsukamoto, "Evaluation function of sensor position for activity recognition considering wearability," in *Proceedings of the ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication (UbiComp '13 Adjunct)*, pp. 623–632, ACM, 2013.

[34] Y. Z. Chong, "Full body wearable instrumented motion analysis system," in *Proceedings of the 3rd International Conference on Bioinformatics and Biomedical Engineering (ICBBE '09)*, pp. 1–4, Beijing, China, June 2009.

[35] J. Knight, D. Deen-Williams, T. Arvanitis et al., "Assessing the wearability of wearable computers," in *Proceedings of the 10th IEEE International Symposium on Wearable Computers*, pp. 75–82, October 2006.

[36] H. D. Fraser, S. Fels, and R. Pritchard, "Walk the walk, talk the talk," in *Proceedings of the 12th IEEE International Symposium on Wearable Computers (ISWC '08)*, pp. 117–118, IEEE Computer Society, Pittsburgh, Pa, USA, September-October 2008.

[37] A. Teller, "A platform for wearable physiological computing," *Interacting with Computers*, vol. 16, no. 5, pp. 917–937, 2004.

[38] R. Haratian, R. Twycross-Lewis, T. Timotijevic, and C. Phillips, "Toward flexibility in sensor placement for motion capture systems: a signal processing approach," *IEEE Sensors Journal*, vol. 14, no. 3, pp. 701–709, 2014.

[39] B. Maciá and J. Llorca, "Sensor for acquiring physiological signals," EP Patent Application EP20,110,782,449, 2013.

[40] F. J. Martinez-Tabares, E. Delgado-Trejos, and G. Castellanos-Dominguez, "Wearable and superhydrophobic hardware for ambulatory biopotential acquisition," in *Proceedings of the 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC '13)*, pp. 1847–1850, IEEE, Osaka, Japan, July 2013.

[41] H. Lee and J. Kwon, "Combining context-awareness with wearable computing for emotion-based contents service," *International Journal of Advances in Science and Technology*, vol. 22, pp. 13–24, 2010.

[42] U. Anliker, J. A. Ward, P. Lukowicz et al., "AMON: a wearable multiparameter medical monitoring and alert system," *IEEE Transactions on Information Technology in Biomedicine*, vol. 8, no. 4, pp. 415–427, 2004.

[43] H. Noma, A. Ohmura, N. Kuwahara, and K. Kogure, "Wearable sensors for auto-event-recording on medical nursing—user study of ergonomic design," in *Proceedings of the 8th International Symposium on Wearable Computers (ISWC '04)*, vol. 1, pp. 8–15, Arlington, Va, USA, October-November 2004.

[44] M. Iqbal, M. Naeem, A. Anpalagan, A. Ahmed, and M. Azam, "Wireless sensor network optimization: multi-objective paradigm," *Sensors*, vol. 15, no. 7, pp. 17572–17620, 2015.

[45] G. A. F. Seber and A. J. Lee, *Linear Regression Analysis*, Wiley Series in Probability and Statistics, Wiley-Interscience, New York, NY, USA, 2003.

[46] G. Bebis and M. Georgiopoulos, "Feed-forward neural networks," *IEEE Potentials*, vol. 13, pp. 27–31, 1994.

[47] R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Structural and Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, 2004.

[48] T. Venckunas, E. Trinkunas, S. Kamandulis, J. Poderys, A. Grunovas, and M. Brazaitis, "Effect of lower body compression garments on hemodynamics in response to running session," *The Scientific World Journal*, vol. 2014, Article ID 353040, 10 pages, 2014.

[49] A. Loewe, W. H. W. Schulze, Y. Jiang, M. Wilhelms, and O. Dössel, "Determination of optimal electrode positions of a wearable ECG monitoring system for detection of myocardial ischemia: a simulation study," in *Proceedings of the Computing in Cardiology*, pp. 741–744, Hangzhou, China, September 2011.

[50] Celbit, "Electrodoctor device, CELBIT LTDA," 2014, http://www.celbit.net/.

[51] H. Naseri and M. R. Homaeinezhad, "Electrocardiogram signal quality assessment using an artificially reconstructed target lead," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 18, no. 10, pp. 1126–1141, 2015.

[52] P. Gupta, P. Srivastava, S. Bhardwaj, and V. Bhateja, "A novel full reference image quality index for color images," in *Proceedings of the International Conference on Information Systems Design and Intelligent Applications 2012 (INDIA 2012) held in Visakhapatnam, India, January 2012*, vol. 132 of *Advances in Intelligent and Soft Computing*, pp. 245–253, Springer, Berlin, Germany, 2012.

[53] J. F. Knight, D. D. Williams, T. N. Arvanitis et al., *Wearability Assessment of a Mobile Augmented Reality System*, 2006, http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.85.8607.

[54] E. J. M. Pearson, "Comfort and its measurement-a literature review," *Disability and Rehabilitation: Assistive Technology*, vol. 4, no. 5, pp. 301–310, 2009.

[55] J. Ortiz, *Smartphone-Based Human Activity Recognition*, Springer Theses, Springer, 2015.

[56] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[57] S. Wang, M. Li, J. Wu et al., "Mechanics of epidermal electronics," *Journal of Applied Mechanics*, vol. 79, no. 3, Article ID 031022, 2012.

[58] M. M. Baig, H. Gholamhosseini, and M. J. Connolly, "A comprehensive survey of wearable and wireless ECG monitoring systems for older adults," *Medical and Biological Engineering and Computing*, vol. 51, no. 5, pp. 485–495, 2013.