Artificial intelligence in diabetes care: the challenge of supporting patients in their daily living

M. Elena Hernando

Biomedical Engineering and Telemedicine Group
Universidad Politécnica de Madrid
GBT-UPM

- Universidad Politécnica de Madrid
  - 42000 students
  - 3.043 teaching and research staff
  - 18 schools and faculties

- Telecommunication School
  - 250 professors
  - 2800 students

- The GBT (Grupo de Bioingeniería y Telemedicina) was founded in 1983
Membership to Research Centers

- Biomedical Research Networking Center in Bioengineering, Biomaterials and Nanomedicine (CIBER-BBN), ISCIII

- Founder of the Centre for Biomedical Technology (CTB) of the Technical University of Madrid
Research Lines: ICT and Bioengineering

- Telemedicine and Smart devices ✓
- Artificial Pancreas ✓
- Biomedical image
- Virtual surgery and surgical planning
- Neureorehabilitation engineering
GBT activities in diabetes began at the 1980’s with an active participation in National and European research programs:

- **TELEMEDICINE** 1989-1991
- **EURODIABETA** 1989-1991
- **TIDDM** 1995-1999 ✓
- **M2DM** 2000-2002 ✓
- **INCA** 2003-2005 ✓
- **MOBIGUIDE** 2011-2015 ✓
- **ELCAP** 2017-2019 ✓
- **DIACRONO** 1997-1999 ✓
- **Red Telem.** 2003-2006
gs
- **PARIS** 2005-2008 ✓
- **PREDIRCAM** 2008-2009
gs
- **Advising** 2007-2009 ✓
- **Econsulta** 2009-2010
gs
- **A PRIORI** 2010-2012 ✓
- **SINEDIE** 2011-2013 ✓
- **FIT-CLOOP** 2005-2017 ✓
Diabetes and Artificial Intelligence

- Diabetes is a complex disease
- Healthcare professionals and patients have to work together to achieve a good metabolic control
- Patients need to have the knowledge to make decisions adapted to their daily living
- AI applications make possible to support patients’ decisions at any scenario
- AI opens the door to react at time scales smaller than the programmed face-to-face visits times
### Expert systems
- Rule-based reasoning (RBR)
- Case-based reasoning (CBR)
- Fuzzy logic (FL)

### Machine Learning
- Artificial neural networks (ANN)
- Genetic algorithms (GA)
- Decision trees (DT)
- Support vector machines (SVM)
# AI in diabetes: overview

- **Expert systems**
  - Rule-based reasoning (RBR): 1
  - Case-based reasoning (CBR): 7
  - Fuzzy logic (FL): 14

- **Machine Learning**
  - Artificial neural networks (ANN): 19
  - Genetic algorithms (GA): 10
  - Decision trees (DT): 8
  - Support vector machines (SVM): 2

<table>
<thead>
<tr>
<th>Method</th>
<th>Application</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBR</td>
<td>Decision support</td>
<td>Suchet et al.</td>
</tr>
<tr>
<td></td>
<td>Debates conference</td>
<td>Friedman et al.</td>
</tr>
<tr>
<td>CBR</td>
<td>Rule-based reasoning (RBR)</td>
<td>Milborrow et al.</td>
</tr>
<tr>
<td></td>
<td>Case-based reasoning (CBR)</td>
<td>Kelly et al.</td>
</tr>
<tr>
<td></td>
<td>Fuzzy logic (FL)</td>
<td>Mangion et al.</td>
</tr>
<tr>
<td>FL</td>
<td>Expert system</td>
<td>Mangion et al.</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>* *</td>
</tr>
<tr>
<td>Machine</td>
<td>Machine learning</td>
<td></td>
</tr>
<tr>
<td>Learning</td>
<td>Artificial neural networks (ANN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>* *</td>
</tr>
<tr>
<td>ANN</td>
<td>Diagnosis</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Diabetes</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>* *</td>
</tr>
<tr>
<td>GA</td>
<td>Prediction of diabetes-related complications</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>* *</td>
</tr>
<tr>
<td>SVM</td>
<td>Prediction of disease-related classifications</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>* *</td>
</tr>
<tr>
<td>DT</td>
<td>Prediabetes</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>* *</td>
</tr>
<tr>
<td>SVM</td>
<td>Prediabetes</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>* *</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>* *</td>
</tr>
</tbody>
</table>
AI in diabetes: applications

- Albuminuria screening
- Automated control
- BG pattern detection in pump users
- BG classification
- Bolus calculator
- Bone mineral density prediction in type 1 DM
- Cardiac autonomic neuropathy assessment
- Cardiovascular risk
- Decision support
- Diabetes diagnosis
- Diabetic retinopathy detection
- Estimation of model parameters
- Foot ulcer prediction
- Foot ulcers risk
- Glucose prediction

- Hypoglycemia detection
- Insulin dose recommendation
- Liver cancer prediction in type 2 DM
- Peripheral neuropathy assessment
- Prediction of DM regression after surgery
- Prediction of macrosomia and gestational DM
- Prediction of prediabetes and diabetes
- PreDM/DM screening
- Renal failure prediction
- Risk of complications
- Type 2 DM treatment suggestions
- Type 2 DM screening
AI in diabetes: applications

- **AI applications** (60)
  - Diagnosis / Assessment: 25
  - Risk / complications prediction: 12
  - Automated control: 6
  - Modeling: 5
  - Self-management Decision Support: 5
  - Glucose prediction: 4
  - Therapeutic Decision Support: 3

PATIENT’S DS 9
.... to support patients’ decisions at any scenario of their daily living
GBT Personal assistants for patients with diabetes


DIACRONO: Ambulatory patient aid (1987)

DIACRONO (1987)

- Patients´ aid in ambulatory decisión making
  - **Self-monitoring**: glucose, insulin, diet, physical activity, other events
  - Therapy consultation
  - Reminders
  - Real time advising

- Portable microcomputer:
  - Microcontroller
  - Assembler programming
  - PC point-to-point connection

DIACRONO (1987): Advising procedures

- Insulin adjustment
  - Skyler’s algorithms
    - **IF** hyperglycemia is evident* for at least 2 days
    - **THEN** do an incremental insulin adjustment

* Alterations in food intake or activity cannot explain out-of-range BG values

- Simplified rule KBS
  - Limited capacity of memory and processing => 50 rules
  - Real time updating from patient self-monitoring data
  - Seamless execution

---

Limitations

- Manual data entrance
- PC point-to-point communication
- Organizational issues
  - Limited access to computers at the hospital
  - High acceptance by patients but professionals were reluctant: workload increment
- Non-commercial hardware:
  - Limited number of units
  - Data persistence only in the device between visits
TELEDIACRONO: Telemedicine patient aid (1990)

TELE-DIACRONO (1990)

- **Point-to-point telephone connection**
- **Experts’ feedback** to patients
  - Messaging
  - Therapy modifications

Telemedicine patient aid (1994)

- Limitations
  - Telemedicine generates huge amounts of data
    - Professionals workload

- AI opportunities: self-monitoring data analysis:
  - Doctors’ support in therapy planning
  - Automatic alarm generation

- Challenge
  - Data incompleteness and uncertainty

- Proposed solutions
  - Causal Probabilistic Networks
  - Qualitative metabolic modeling
DIABTel (1996)

- Commercial HW + external modem
- Glucose meter communication (OneTouch, Lifescan)
- Increased data quality

(1997)

- MSDOS
- HP 200LX Intel 80C186
- RS232

Clinical evaluation
- 10 T1DM patients
- 6-month cross-over study
- 3524 BG readings
- 1649 day-to-day insulin adjustments
- 0.5% HbA1c reduction
- Internet !!!
  - Phone-based: modem, GSM connections, ....
  - Web applications
  - Multiplatform applications (Java, JVM)

- DIABTel multiaccess (1998)
- INCA (2003-2005)

DIABTel (2000)
Pocket PC
Epoc32 (Symbian)

M2DM (2002)

INCA PA (2003)
Knowledge Management

- Triggered by data reception
- Automatic summaries and alarms
- Combined techniques (data availability)
  - Statistics
  - Rule-based
    - Hypoglycaemia status
    - Hyperglycaemia status
    - Oscillating status
    - Hyper-insulinitation
  - Model-based CPN
    - Insulin effectiveness at ‘breakfast’, ‘lunch’, ‘dinner’, ‘night’
    - Therapy advisor
Retrospective evaluation
- 11 patients that used the M2DM telemedicine service during one year
- Detection of abnormal data in 37% of transmissions
- 100% of anomalous situations were detected (cases where a therapy modification was decided by the healthcare professional)

- Instantaneous feedback to patients reinforces the education and the motivation aspects of the therapy
- Decrease of professionals’ workload due to telemedicine
- It focuses doctors’ and patients’ attention on abnormal data
- More powerful portable devices
  - Distribution of the intelligence
- Direct communication with Continuous Glucose Monitoring systems: Reaction in real time
- Data from different sources: BG, CGM, insulin pumps
- AI opportunities:
  - Combination of multiparametric data
  - Enrich data: Mealtime BG classification
  - Glucose prediction using CGM sensors
  - Artificial pancreas
  - Physical activity identification
INtelligent Control Assistant for Diabetes (2003-2005)

- **Goal:** To create an **intelligent mobile Personal Assistant** for continuous self-monitoring glucose and subcutaneous insulin infusion integrated into a telemedicine diabetes management service.

Blood glucose classifiers

- Comparison of mealtime BG classifiers
  - Fixed-time intervals
  - Rules from experts
    
    \[
    \text{IF Measurement time is Breakfast AND Time difference with previous measurement is Zero THEN Classification\_Result is Breakfast-Preprandial}
    \]
    
    \[
    \text{IF Measurement time is Breakfast AND Time difference with previous measurement is High THEN Classification\_Result is Breakfast-Postprandial}
    \]
  - Expert rules + Rules induced from data
    - Fuzzy Decision Tree (FDT)
    - Automatic generation of rules
    - Consistency checking, redundancies removal
    - Compact and understandable variables and rules
Fuzzy Rule-Based Classifier

- **Patient**
- **BG data**
- **Insulin data**

**Input variables**
- BG Time
- BG Value
- Time Difference with previous measure

**Insulin bolus administered close to a BG measurement**

**FUZZY RULE-BASED CLASSIFIER**

- Expert Knowledge
- Induced Knowledge

**Classification Results**
- Breakfast Preprandial
- Breakfast Postprandial
- Lunch Preprandial
- Lunch Postprandial
- Dinner Preprandial
- Dinner Postprandial
- Night
- Morning
- Afternoon
- Repeated
Fuzzy Rule-Based Classifier: Results

- Data set: 10 DMT1 patients, 4 months, 4240 BG meas.
- Training data set + test dataset

<table>
<thead>
<tr>
<th></th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed-time intervals</td>
<td>73.34%</td>
</tr>
<tr>
<td>Rules from experts</td>
<td>63.7%</td>
</tr>
<tr>
<td>FRBC</td>
<td>83.2%</td>
</tr>
</tbody>
</table>

- Integrated into the KM agent
- Extra computation time for a week of data: 1” to 3”

best adjustment for each patient:

same classifier for all the patients:
Glucose prediction

Goal: Glucose prediction from CGM sensor data

Artificial neural networks

Physical activity

Responses to exercise in T1D

a) General factors that impact in glucose
   - Intensity, duration and type (aerobic, anaerobic)
   - Others: e.g. fitness level or previous meals

b) Specific for T1D
   - Plasma insulin

<table>
<thead>
<tr>
<th>Plasma insulin</th>
<th>Hepatic glucose production</th>
<th>Muscle glucose uptake</th>
<th>Trend in glycaemia</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Ṫ↑↑</td>
<td>↑</td>
<td>↑ or ↑↑</td>
<td>Hyperglycaemia</td>
</tr>
<tr>
<td>Normal</td>
<td>Ṫ↑↑</td>
<td>↑↑↑</td>
<td>→ or ↓</td>
<td>Limited</td>
</tr>
<tr>
<td>High</td>
<td>↑</td>
<td>↑↑↑</td>
<td>↓ or ↓</td>
<td>Hypoglycaemia</td>
</tr>
</tbody>
</table>
Physical Activity monitoring techniques

- **Indirect calorimetry** = Determine respiratory gas fluxes (O2, CO2)
  - ✓ ‘Gold standard’: accuracy and precision
  - ✗ Laboratory set-ups only

- **Doubly labelled water** = Measure elimination of $^2$H, $^{18}$O tracers
  - ✓ ‘Gold standard’: accuracy and precision
  - ✗ Lack of temporal resolution

- **Heart rate (HR) monitors**
  - ✓ Physiological response
  - ✗ Factors other than PA altering HR

- **Accelerometers** = Sense motion
  - ✓ Objective quantification of body movements in multiple axes
  - ✗ Complicated signal patterns
  - ✗ Not sensitive to PA which does not lead to sensor movement
Combining information sources

Accelerometry = Motion mechanics + HR = Physiological response to PA

- Merging sources for a more complete characterization of PA
- Sports scientist advocate for this combination
  
  [Freedson and Miller, 2000; Ainslie et al., 2003; Corder et al., 2005; Plasqui and Westerterp, 2005, 2006, 2007; Valanou et al., 2006; Westerterp, 2009]

Make use of machine learning (ML) capabilities

- ML to facilitate the recognition of complex patterns in multi-modal signals
Dataset overview

- Data stratified in **3 standard PA intensity levels** = MET values from Ainsworth et al. [2000]’s Compendium:
  - Sedentary & low-intensity: <3 MET
  - Moderate: 3-6 MET
  - Vigorous: >6 MET

<table>
<thead>
<tr>
<th>PA intensity</th>
<th>Total (n=16) 92 sessions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>117.1h (65.5%)</td>
</tr>
<tr>
<td>Moderate</td>
<td>33.9h (19.0%)</td>
</tr>
<tr>
<td>Vigorous</td>
<td>27.7h (15.5%)</td>
</tr>
</tbody>
</table>

- Information about the predominant **exercise modality**: sustained aerobic, mixed or resistance

<table>
<thead>
<tr>
<th>PA modality</th>
<th>Total (n=10) 25 sessions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sustained aerobic</td>
<td>6.8h (40.0%)</td>
</tr>
<tr>
<td>Mixed</td>
<td>3.5h (20.3%)</td>
</tr>
<tr>
<td>Resistance</td>
<td>6.7h (39.7%)</td>
</tr>
</tbody>
</table>
Results - Performance in classification

Best performance = Wrapper (Genetic) + Bagging

- Recognition scores (SBSCV): up to **85.17%** for intensity, **97.90%** for modality identification
- Generalization scores (LOSOCV): up to **84.65%**
- Temporal filter (HMM) successfully exploited temporal redundancies
Results - Time courses

- Wrapper(Genetic)+Bagging

Applications
- Objective physical activity monitoring (vs self-reporting)
- Improvement of BG predictors
- Patients’ metabolic modeling
- Artificial pancreas
Physical Activity objective monitoring

- Internal accelerometer and heart rate band

**AppSiMe**

- Smartwatch with internal accelerometer and heart rate sensor
**Goal:** Ubiquitous, user-friendly, patient-centered mobile decision-support system for patients and for their care providers, based on the continuous application of clinical guidelines and on semantically integrated electronic health records

**Cases:** Atrial fibrilation

Gestational diabetes
Patient workflows

**Figure 3.** Example of patient advice associated with the workflow blood glucose (BG) monitoring. Monitoring advice: (2a) Reminder to monitor BG and (2b) messages to acknowledge compliance or to reinforce compliance. Clinical assessment advice: (3a) Inform about therapy change and (3b) ask to contact the hospital to reinforce education.
Mobiguide

- Mobile decision support (mDSS)
- Communication with medical devices
  - BG, BP, ECG

To assure a correct monitorization you must remain resting while the process take place and the Bioharness belt should be ON and correctly placed.

For instructions on how to place the belt and starting it please press the info button (!) of the top bar.

Session Goal: 00:30:00
Elapsed time: 00:00:43

Start time: 16:38:00
Elapsed time: 00:00:27

Current Level: Moderate

Average Level: Moderate

- 42 steps
- 121 bpm
- 1.26 kcal

MobiGuide
Guiding patients anytime everywhere
Mobiguide: results of the clinical study

- Patients: 17 GDM at Sabadell Hospital, Barcelona

- Satisfaction evaluation
  - **CLINICIANS**
    - Clinicians agreed that MobiGuide helps them in identifying priorities and increases patient safety via its data quality awareness.
    - Two thirds of GDM clinicians agreed that the system makes it easier to manage patients.
  - **PATIENTS**
    - Two thirds (12/17) of the patients provided positive ratings of 4 or 5 for confidence provided by the system.
    - Two thirds of the patients liked the system’s ability to adapt to context.
    - 12/14 patients reported their intention to use the system in the future.
    - Most patients (15/17) agreed that the system has not complicated their lives.
Intelligent system for the management of diabetes diagnosed during pregnancy

- Decision support for clinicians and patients:
  - Clinicians:
    - Patients are prioritized according to their metabolic condition
    - Therapy suggestions (insulin needs)
  - Patients:
    - Instant feedback
    - Data completion
    - Automatic diet prescription and detection of insulin needs
- Glycaemia data from glucose meters + ketonuria and dietary treatment compliance
- Clinical study: Sabadell Hospital and Mutua de Tarrassa
  - 17 months
  - 119 patients with GDM (80 intervention + 39 control)
BG Classification: C4.5 decision tree
7 input features

Metabolic Condition: Two Moore machines
(finite deterministic automaton)

DS Tool: Logic rule set
Sinedie: BG classification

- C4.5 decision tree
- 7 input features
  - wrapper evaluator
  - genetic search algorithm

- Trained with retrospective data from 25 patients

- Performance during the Sinedie clinical study

- 80 patients
  - 13870 glycaemia meas. uploaded by patients
  - 98.63% of the measurements were correctly classified vs 78.00% with pre-defined mealtimes
Sinedie: Patient’s Metabolic Condition

- Two more machines (finite deterministic automataons)
  - Glucose: 24 states (Normal, altered, important alteration)
  - Ketonuria: 7 states (positive, negative)

- Presentation to healthcare professionals

<table>
<thead>
<tr>
<th>History number</th>
<th>Name</th>
<th>Surname</th>
<th>Insulin</th>
<th>State</th>
<th>Last communication</th>
<th>Last recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>00000001</td>
<td>PATIENT</td>
<td>SUR1</td>
<td></td>
<td>SIGNIFICANTLY ALTERED</td>
<td>30/05/15 - 00:08</td>
<td>29/05/15</td>
</tr>
<tr>
<td>00000002</td>
<td>PATIENT</td>
<td>SUR2</td>
<td></td>
<td>ALTERED</td>
<td>29/05/15 - 21:57</td>
<td></td>
</tr>
<tr>
<td>00000003</td>
<td>PATIENT</td>
<td>SUR3</td>
<td></td>
<td>Increase 0.5HC night</td>
<td>27/05/15 - 12:58</td>
<td>27/05/15</td>
</tr>
<tr>
<td>00000004</td>
<td>PATIENT</td>
<td>SUR4</td>
<td></td>
<td>NORMAL</td>
<td>26/05/15 - 22:06</td>
<td></td>
</tr>
<tr>
<td>00000005</td>
<td>PATIENT</td>
<td>SUR5</td>
<td></td>
<td>Reinforce diet compliance</td>
<td>26/05/15 - 21:00</td>
<td>26/05/15</td>
</tr>
<tr>
<td>00000006</td>
<td>PATIENT</td>
<td>SUR6</td>
<td></td>
<td>Evaluate start of insulin: Slow NIG, fast DIN</td>
<td>26/05/15 - 17:57</td>
<td>26/05/15</td>
</tr>
<tr>
<td>00000007</td>
<td>PATIENT</td>
<td>SUR7</td>
<td></td>
<td>ALTERED</td>
<td>25/05/15 - 23:02</td>
<td>11/05/15</td>
</tr>
<tr>
<td>00000008</td>
<td>PATIENT</td>
<td>SUR8</td>
<td></td>
<td>Reduce 0.5HC BRK</td>
<td>24/05/15 - 21:28</td>
<td>24/05/15</td>
</tr>
</tbody>
</table>
Sinedie: Decision support tool

- Automatic diet modifications => patients

  IF ‘Deficient MC due to 2 hyperglycaemias in breakfast postprandial_andnegative ketonuria state’
  AND ‘no_previous_diet_adjustments_by_hyperlycemia’
  AND ‘treatment_reading_not_recent’
  AND ‘previous_recommendation_not_recent’
  THEN ‘reduce carbohydrates at breakfast’

- A new diet therapy is created and notified to the patient
Sinedie: results

- Reduction in face-to-face visits: 80.75%
- Reduction in professionals workload: 36.7%
- Similar clinical outcomes
- Patients acceptance

- My general feeling is good
- I am confident in being well controlled
- I am satisfied with my diabetes follow-up
- The system use reduce the visits to the hospital
- The number of face-to-face visits was sufficient
- The systems helps to analyse my glucose data
- The educational materials are useful to increase my knowledge
- I frequently used the educational materials
- I would recommend the system
- The sysem does not complicates my daily life
- I do not feel pressed to send data frequently
- Therapy changes are presented in a clear way
- Learning the system is easy
- The system is usefull
Conclusions: new opportunities for AI in diabetes

- The diabetes management paradigm is being transformed by the combination of continuous glucose monitoring and insulin pump data.
- Additionally, current wearable technologies allow to monitor other physiological parameters (i.e. heart rate, sleep quality, physical activity, etc) that have a close relationship with metabolic control.
- Nowadays, the challenge is to create proactive AI systems, integrated in the healthcare information systems, accessible from patients’ devices and able to collect relevant multi-parametric data from patients in a seamless way.
Thanks to the diabetes technology team

Thank you for your attention!
Artificial intelligence in diabetes care: the challenge of supporting patients in their daily living

M. Elena Hernando

Biomedical Engineering and Telemedicine Group
Universidad Politécnica de Madrid