Intelligent agents in home healthcare

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Abstract The percentage of the population who are elderly will significantly increase over the next decade due to the aging of the baby-boom generation, putting additional stress on healthcare. The elderly are at higher risk for many disorders, especially cardiac-related problems and diminishing mental capacity. The impact will be felt in various domains, including additional pressures on existing infrastructure and increasing per capita costs for medical care. A potential approach to alleviate these problems is the implementation of home healthcare using new technologies. With remote interventions, the patient can remain at home, not only reducing costs but also benefiting from a familiar environment and support of family members. Methods are outlined that can contribute to the delivery of home healthcare in the areas of monitoring and support using intelligent agent methodologies. The methods are illustrated in two distinct applications: support and intervention for patients with dementia and remote monitoring of cardiac conditions. The methods outlined can also be adapted for use in other areas.

Keywords Assistive technologies · Intelligent agents · Home healthcare · Telemedicine

1 Introduction

With the aging of the baby-boom generation, the percentage of the population who are elderly will increase dramatically over the next decade. Remote monitoring and healthcare interventions of elderly patients will become increasingly

crucial to assure the safety of patients living at home, reduce the costs of healthcare delivery, and serve those who live large distances from care facilities. This growing population will be susceptible to diseases associated with aging, including declining mental abilities and dementia, as well as physical problems. Dementia is a serious concern in terms of its impact on the patient, the family, and the healthcare system. Alzheimer's disease and other dementias present an especially serious challenge due to the relentless, progressive nature of the disease. Some technologies currently exist for providing remote healthcare in this population, but new methods are needed to further address the growing need [1].

New advances in technology directed toward home healthcare have set the stage for innovative use of technology for individualized care. During the last decade, telemedicine applications have become common for consultations such as radiology and dermatology [2]. These applications in general require elaborate equipment and high-speed transmissions. Recently, applications have been developed, mostly for the geriatric population that use simple devices based on standard telephone communications, simple monitors, and inexpensive video cameras that permit the medical professional to observe and interact with the patient [3]. The same communication line can be used to transmit basic vital signs such as blood pressure and glucose levels. Adapting simple, inexpensive equipment to support patients with diminished mental capacity requires an additional level of sophistication to cope with the mental status of each individual patient.

The methods described here are designed to cover multiple aspects of care for the elderly patient and can be individualized according to the needs and capabilities of each patient. The implementation of home-based support using ordinary technology can allow patients to remain in their home environments for longer periods of time.

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Potential benefits include increased quality of life for patients living in familiar surroundings and maintenance of some level of independence, reduction on the burden of caregivers, and lowering of societal costs by delaying the need for institutional care [4].

Digital intervention for assisted living includes a comprehensive patient-oriented approach. Methods of communication can include a telephone call, a video suggestion that can be made using a television, or verbal prompting that does not rely on the patient answering the telephone. These goals can be accomplished using currently available high-speed communications and existing electronic devices. Intelligent agent software can coordinate support and surveillance capabilities. An offshoot of distributed artificial intelligence, the intelligent agent approach has been used successfully in a number of applications including healthcare delivery [5]. The agents themselves provide reasoning capabilities through a variety of methodologies including artificial intelligence based models, Bayesian models, neural networks, and other reasoning paradigms. An existing agent system developed by our research group can be tailored to the specific tasks of this application [6]. Artificial intelligence techniques and neural network modeling have also been used to address problems of dementia [7] but mainly as diagnostic tools. Design of intelligent systems that can take advantage of existing devices have the potential for assisting the patient as well as caregivers and family members.

Cardiac problems also pose increased risk in the elderly community. Many telemedicine systems have been developed for remote monitoring of electrocardiograms (ECGs) and other vital signs such as blood pressure. In the work described here, automated algorithms are described that can perform detailed analyses on these transmitted data and determine if an office visit or further intervention is required [8].

2 Software methodology

2.1 Intelligent agent methodology

The intelligent agent approach provides a broad framework for the development of computerized systems that can act independently in collecting information and automatically implementing actions. Intelligent agents extend the idea of hybrid systems in which differing approaches are combined to reach a comprehensive decision [9]. The intelligent agent approach has the advantage of incorporating a wide-ranging combination of types of information and different paradigms without internal modification to any of the component agents. Figure 1 shows an intelligent agent configuration for decision support. The principal parts of the control structure are the task manager and the communications

Fig. 1 Components of intelligent agent system

interface. The task manager breaks the problem into subtasks that are then directed toward the appropriate agents. It also combines results from agents, including the client, for the overall response to the problem. The communicator must present input to each agent in a form that it can understand and interpret output from each agent so that other relevant agents can understand it. The remainder of the structure is contained in the agents themselves. The agents may use one or more methodologies, including three decision paradigms developed by our research group: the components include a knowledge-based component that incorporates expert supplied rules, a data-based component that permits learning from data, and a signal analyzer to interpret biosignals and sensor output. The primary components are outlined below.

2.1.1 Knowledge-based system

EMERGE is used as the knowledge-based component [10]. The knowledge base relies on rules developed through expert consultation. EMERGE functions as an independent agent that acts on domain knowledge in symbolic form. The task manager described above also uses the EMERGE inference engine to process of Meta rules that coordinate actions of the agents. EMERGE uses approximate reasoning to determine if each individual rule is substantiated by current data. The rule format is:

	Premise	Relative importance	Degree of presence in current case
IF	P1	w1	d1
	P2	w2	d2
	·		
	·		
	·		
	Pn	wn	dn

THEN Conclusion, Threshold T

The evidence (E) is aggregated using the formula:

$$E = \sum_{i=1}^n w_i d_i / 10 \quad (1)$$

The rule is substantiated if $E > T$. The information gained from this process is twofold:

Substantiation or non-substantiation of the rule
Degree to which the rule has been substantiated,
determined by the normalized value:

$$\delta = (E - T)/(1 - T) \quad (2)$$

where δ is a value in the unit interval.

The weights w_i are normalized in the unit interval [0, 1] and sum to 1. The values for d_i are between 0 and 10, inclusive, and are also normalized in [0, 1] for computational purposes. Rules are used to analyze specific situations and to provide suggested actions. Examples are given in the “Applications” Section.

2.1.2 Neural network model

The neural network model is based on the Hypernet system developed by the authors [11]. Hypernet is used to develop a decision model based on data-derived knowledge. It produces both a decision as well as weighting factors for the parameters used to reach the decision. The method used in Hypernet is a modification of the potential function approach to pattern recognition. Rather than using the Euclidean distance formula, the potential function is used:

$$P(x, x_k) = \sum_{i=1}^{\infty} \lambda_i \Phi_i(x) \Phi_i(x_k) \quad (3)$$

for $k=1,2,3,\dots$, where $\mathbf{x}$ is a feature vector, $\Phi_i(\mathbf{x})$ are orthogonal functions and λ_i are non-zero real numbers. P_1 is computed by substituting the values from the first feature vector for case 1, $\mathbf{x}_1$. Subsequent values for P_k are then computed by

$$P_k = P_{k-1} + r_k P(x, x_k) \quad (4)$$

where

$$r_k = \begin{cases} 1 & \text{If } P_i < 0 \text{ and class 1} \\ -1 & \text{If } P_i > 0 \text{ and class 2} \\ 0 & \text{If } P_i > 0 \text{ and class 1 or } P_i < 0 \text{ and class 2} \end{cases}$$

The functions used in Hypernet are chosen from the set of multidimensional orthogonal functions developed by Cohen [12]. To avoid over-fitting of the data, in general, the first-order terms along with the interactive terms are used:

$$D(x) = \sum_{i=1}^n w_i x_i + \sum_{i=1}^n \sum_{\substack{j=1 \\ i \neq j}}^n w_{i,j} x_i x_j \quad (5)$$

Classification is accomplished using:

$D(y) > 0$ implies substantiation of the condition
 $D(y) < 0$ implies non-substantiation of the condition
 $D(y) = 0$ indeterminate

The degree of confidence is determined by comparing results from the decision equation $D(y)$ where y represents the values for each parameter for the current patient visit with $D(x)$, the decision surface. The further the $D(y)$ is from $D(x)$, the more certain that the classification is correct. The degree of confidence for this method is defined by the normalized value:

$$\delta = |D(y) - D(x)|/D(z) \quad (6)$$

where z is the vector whose components result in the greatest distance from $D(x)$.

The neural network is feed-forward and consists of three steps: training, testing, and application. It relies on supervised learning using data of known classification.

2.1.3 Chaotic analysis of time series

New methods of nonlinear analysis provide summary measures for biomedical time series, including ECGs and EEGs. These summary measures can be used as parameters in the neural network model. The method is based on the continuous solution of the logistic equation:

$$a_n = A a_{n-1} (1 - a_{n-1}) \quad 2 \leq A \leq 4 \quad (7)$$

At $A=4$, the solution is

$$a_n = 1/2 [1 - T_{2^n}(1 - 2a_0)] \quad (8)$$

where $T_n(x)$ is the Chebyshev function [13].

A useful graph for practical applications is the second-order difference: $(a_{n+2} - a_{n+1})$ vs. $(a_{n+1} - a_n)$, a plot centered at the origin that is useful in modeling dynamic biological parameters, such as hemodynamic flow and heart rate variations. A numerical summary of the second-order difference plot, the central tendency measure (CTM), is a useful parameter that indicates the degree of variability in the time series:

$$\text{CTM} = \sum_{i=1}^{t-2} \tau(d_i) / (t-2) \quad (9)$$

where $\tau(d_i) = \begin{cases} 1 & \text{if } [(a_{i+2} - a_{i+1})^2 + (a_{i+1} - a_i)^2]^{1/2} < r \\ 0 & \text{otherwise} \end{cases}$

Although the CTM on its own has some degree of diagnostic power, the accuracy is improved when used as a parameter in a neural network model combined with other symptoms. When used on its own, the method follows the above patterns.

1. Substantiation of a condition is determined by the $(1 - \text{CTM})$ exceeding a specified threshold T .
2. The certainty of the classification increases with a decrease of the CTM in the unit interval [0, 1].

The degree of confidence $\delta = 1 - \text{CTM}$ while the degree of confidence for non-substantiation is CTM. The smaller

CTM value indicates a higher variability in the second-order difference. Illustrations of the CTM are given in the cardiology application.

2.1.4 Trend analysis

Another useful tool that can be implemented remotely is trend analysis. The method has been implemented for knowledge-based, data-based, chaos-based analysis. New data values are compared with previous values in the patient record to determine if a condition has improved, deteriorated, or stayed the same. Trend analysis is particularly important when remotely monitoring a patient as it can give immediate feedback if a significant change has occurred. The method has been described elsewhere but the general algorithm is included below [14]. Determination of the value for $\delta(t)$, the degree of substantiation at time t , is defined differently for each method as defined above for knowledge-based, data-based, and chaotic analysis.

Trend Analysis Algorithm

For all currently confirmed conditions

If condition i is present at time t_n with $\delta(t_n)=a$

If condition n was previously present with $\delta(t_{n-1})=b$

set $\alpha=a-b$

If condition n was not previously present set $\alpha = a$

If $\alpha > 0$

if $(x_1 < \alpha < x_2)$ then send alert 1

if $(x_2 < \alpha < x_3)$ then send alert 2

if $\alpha > x_3$ then send alert 3

For all previously-confirmed conditions

If condition is not currently present send notification

If condition i is present with $\delta(t_n)=a$

If condition i previously present with $\delta(t_{n-1})= b$

and if $(b-a) > x$

then send notification of change in degree

each other and with the patient, caregiver, and medical professional. The agent system is designed to cover multiple aspects of care for the patient and can be individualized according to the needs and capabilities of each patient. The implementation of home-based support using ordinary technology can allow patients to remain in their home environments for longer periods of time [15]. Potential benefits include increased quality of life for patients living in familiar surroundings and maintaining some level of independence, reduction on burden for caregivers, and lowering of societal costs by delaying the need for institutional care. The potential usefulness of technology in addressing daily needs of the elderly suffering from dementia has been recognized for some time [16]. Technology has been used to interact directly with the patient as well as with the caregiver [17, 18]. Applications include in-home devices as well as tele-medicine interventions [19]. The internet has also been used as a source of information both for education and for support [20]. Projections for the future envision the use of technology to assist both the dementia patient and caregiver in maintaining everyday activities [21]. An integrated system can provide support, directed toward keeping the patient in the home environment as long as possible. The first goal is to permit remote monitoring by a caregiver or medical professional. The second goal is to intervene directly to improve problem behaviors by automatically and remotely providing information or by making suggestions via the integrated system. One benefit of this design is that common problem behaviors in this population that may affect ability to live at home or increase the cost of assisted living can be targeted individually. Basic structures include:

- Reminders to perform daily tasks both automated and triggered by caregivers at a remote location
- Communication with family members and caregivers, both pre-recorded and internet-based to reassure and assist the patient
- Surveillance using sensors, vital sign monitoring, and cameras to assure the well-being of the patient.
- Monitoring of vital signs

The approach consists of the following components: reminders, communication, surveillance, education, and support. Technologies include the following: television, video monitor, computer, telephone, vital signs monitor, web camera, and high-speed internet connection. Sensors can be employed to track activities of each patient.

To determine individual needs patients are evaluated using standard tools for dementia diagnoses. The Combined Folstein Mini Mental Status Exam [22] and the Blessed Dementia Scale [23]. Functional abilities, self-maintenance, and instrumental activities of daily living can be assessed using the Lawton Brody IADL scale [24]. These assess-

3 Applications

3.1 Patients with declining mental abilities

This approach relies on intelligent agent-based software running on a home computer. The agents communicate with

ments determine the types of interventions for various levels of cognitive deficit and functional level.

Background work for this project was done in conjunction with the UCSF Fresno Alzheimer's and Memory Center. Although the center is located in an urban area, the patient population comes from a large rural geographic region. The heterogeneity of the population is evidenced by the ethnic make-up of Fresno County's population which is composed of approximately 350,000 Hispanic, 320,000 white, 40,000 black, 6,000 American Indian, 63,000 Asian, 700 Pacific Islander, 1,500 other, and 19,000 two or more races (2000 US Census). Figure 2 shows the geographical area and its relationship to the state of California. For more than 15 years, the UCSF Fresno Alzheimer's & Memory Center has been one of the ten State of California funded Alzheimer's Diagnostic and Research Centers. UCSF Fresno Alzheimer's and Memory Center's service area includes ten counties encompassing a geographical area of 33,000 miles². There are major metropolitan cities within each county with an average of 15–20 rural towns within each county.

Personal care, interaction with family and community, and anxiety are three general problem areas for dementia patients, all of which tend to lead to patient institutionalization, either by disability leading to patient health and safety issues or by increased caregiver burden leading to burnout. Individual patient needs must be addressed in order to develop patient-specific interventions and evaluation parameters. Table 1 lists the software agents defined according to function and as well as the human agents who will interact with the software agents. Table 2 gives examples of tasks for which agents can provide assistance. The knowledge-based component serves as the basis for coordination of tasks as illustrated in Fig. 1. Depending on the type of data, either the knowledge-based component or the neural network is used to evaluate data and provide feedback.

The user interface requires adjustment based on the capability of patients and caregivers to interact with the system. Figure 3 shows components of the system and input parameters. Software components include features that will automatically interact with the patient to ask the

Fig. 2 Area served by Alzheimer's and memory center

patient to perform tasks, to make suggestions at appropriate times, to provide audio and video reminders, and to monitor responses. The diagram in Fig. 3 also illustrates the sources of information used in the software development.

The initial phase evaluates the ability of both patient and caregiver to interact with the system. The purpose of this evaluation is to make additional adjustment in the system to improve usability. The following outcome variables are measured using five-value Likert scale:

Unsatisfactory	Marginal	Adequate	Very good	Exceptional
1	2	3	4	5

Evaluation focuses on the ability to use or respond to each of the following:

Keyboard	C_1
Mouse	C_2
Touch screen	C_3
Voice commands	C_4
Written commands	C_5

A summary outcome variable, O_1 , indicating the overall usage competence is computed as:

$$O_1 = \sum_{i=1}^5 C_i \quad (10)$$

Each variable C_i is averaged for all patients to indicate competency in each category. An additional outcome variable, O_2 , will focus on the subjects' reaction to different components of the system, and will be measured on a three-value Likert scale:

Frustrated	Neutral	Interested
1	2	3

The parameters are important for both patient and caregiver.

Each variable C_i indicates competency in each category. An additional outcome variable, O_2 , focuses on the subjects' reaction to different components of the system, measured on the same Likert scale described above. Specific components depend on the individual implementation.

3.2 Remote automated analysis of cardiac data

Telemedicine systems are in place to remotely monitor ECGs, blood pressure, and other vital signs. In most telemedicine interventions, these values are monitored manually. More sophisticated remote analysis of these signals can result in the detection of anomalies that could lead to future problems. The three methods described

above, knowledge-based system, neural network, and chaotic analysis, can all be applied in the remote monitoring situation to provide comprehensive analysis. Examples of each are given below.

3.2.1 ECG irregularities

ECGs can be transferred electronically for analysis. The EMERGE program automatically analyzes the ECG along with other information that can be confirmed by remote monitoring [25]. The process is illustrated in the sample rule below:

	Premise	Relative importance
IF	Multiple PVCs	0.4
	BP<90/60	0.2
	Sweating	0.1
	Nausea	0.1
	Dizziness	0.1
	Weak peripheral pulses	0.1

THEN Transfer to hospital, Threshold 0.6

From a remote location, the PVCs can be detected from the transmitted ECG, and the blood pressure and pulse information can also be transmitted. The other three symptoms can be confirmed by questions to the patient or caregiver.

3.2.2 Congestive heart failure

The CTM measure can be used as a strong indicator of congestive heart failure (CHF), with a high value indicating a healthy condition and a low value indicating disease. The CTM is computed using the second-order difference plot as described above. The analysis is based on a Holter recording which is a 24-h ECG, the results of which can be transferred electronically for analysis. While this measure alone is a good indicator, its diagnostic power is increased when combined with a neural network model that contains other clinical parameters [26]. An initial screening is done with the CTM alone. If the CTM is less than 0.7, this is a strong indicator of CHF. However, some CHF patients are found in the usually normal range above 0.7. The resulting sensitivity, specificity, and accuracy are 69%, 91%, and 74%, respectively. When the CTM measure is combined with clinical parameters, these percentages change to 84%, 82%, and 84%. Clinical parameters include: edema, rales, heart rate, and BUN. The neural network model is used to combine the CTM with these clinical parameters. The heart rate and possibly rales can be determined remotely. Another study shows that using multiple CTM measures produces results of 80%, 89%,

Table 1 Agents and devices

Agent	Type	Devices
Reminder	Software	Television, telephone, sensors, video camera
Communication	Software	Wireless network, computer, television
Surveillance	Software	Wireless network, vital signs monitor, video camera
Patient	Human	Television, video cam, telephone
Caregiver	Human	Computer, Internet, telephone, video cam
Medical Professional	Human	Computer, Internet, telephone, video cam

and 85%. These parameters include CTM ($r=0.05$), CTM ($r=0.1$), number of RR intervals, lowest value CTM >0.99 . All of these values can be determined remotely. Note that the neural network model explained above is used to combine the CTM measure with clinical parameters and is also used to combine the multiple CTM measures.

4 Conclusion

Remote access to healthcare can be looked at from a number of viewpoints. Currently, most attempts at home healthcare are disease-focused and involve some form of remote monitoring, such as typical telemedicine applications that check vital signs and ask questions of the patient and/or caregiver. Others are interventional, such as providing internet-accessible information on specific diseases or remote prompting for support for patients living alone who may be suffering from dementia. Both of these types of monitoring can be very beneficial to the patient and the patient's family and also to the healthcare provider in reduction in time and travel. However, added benefits can be achieved if these methods are connected to an electronic record that interfaces with a method for uncovering trends in the patient's health as well as recording new

Fig. 3 Schematic of software

information for each remote encounter. This added step helps the remote healthcare provider to have an in-depth picture of the health of the patient. Many types of remote monitoring accompanied by multiple disease models and methods of analysis will be required to provide this complete picture. In this article, two types of applications are included: one which is chiefly interventional and the other which is chiefly observational. The theoretical methods that are outlined can be adapted to new diseases, but more models will be necessary to convey the complete state of health of the patient and to determine which interventions are necessary, whether they are remotely administered or require direct patient care.

The methods described here are particularly useful for patients living in rural areas, as well as relatives who may live some distance from their elderly family members. Remote access can help to identify potential problems and can also be used for communication among family members. These methods can allow patients to live in the home environment longer resulting in reduced costs and improved quality of life. Many obstacles remain in completing the implementation of these methods including logistical, financial, and technical issues.

Table 2 Design features

Problem area	Intervention	Evaluation parameters
Personal care	Alerting to initiate tasks	Task completion
Meal preparation	Alerting to complete tasks	1: completed 1st attempt, 2: completed after reminder
Bathing	Sensing job completion Alerting if not completed	3: did not complete
Inability to keep appointments	Morning alerting system Calendar alerting system	Ability to keep phone appointments 1: never, 2: occasional, 3: sometimes, 4: often, 5: always
Repeated phone calls to family members	Sensing repeated dialing Alerting for repeated phoning Pre-recorded video messages, updatable Web	Number of repeated phone calls 1: increased, 2: no change, 3: decreased
Individual problems	Individualized intervention	Individualized evaluation parameters

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References

- Hudson DL, Cohen ME (2006) Intelligent agent model for remote support of rural healthcare for the elderly. *IEEE Eng Med Biol* 28:6332–6335
- Smith AC, Bensink M, Armfield N, Stillman J, Caffery L (2005) Telemedicine and rural health care applications. *J Postgrad Med* 51(4):286–293
- Topo P (1998) Technology in everyday life and care of elderly living at home and suffering from dementia. *Stud Health Technol Inform* 48:320–323
- Banerjee SJ, Murray J et al (2003) Predictors of institutionalisation in people with dementia. *J Neurol Neurosurg Psychiatry* 74(9):1315–1316
- Lanzola G, Gatti L, Falasconi S, Stefanelli M (1999) A framework for building cooperative software agents in medical applications. *Artif Intell Med* 16:223–249
- Hudson DL, Cohen ME (2001) Intelligent agents in medical systems. *ISCA Conf Intell Syst* 10:9–12
- Cohen ME, Hudson DL (2001) Consequential reasoning in Alzheimer's disease. *ISCA Intelligent Systems* 10:5–8
- Hudson DL, Cohen ME (2002) Use of intelligent agents in the diagnosis of cardiac disorders. *Comput Cardiol* 29:633–636
- Hudson DL, Cohen ME, Deedwania PC (1995) Hybrid system for diagnosis and treatment of heart disease. In: Cohen ME, Hudson DL (eds) *Comparative Approaches to Medical Reasoning*. World Scientific, Singapore, pp 289–310
- Hudson DL, Cohen ME (1999) *Neural Networks and Artificial Intelligence in Biomedical Engineering*. Wiley, Hoboken
- Cohen ME, Hudson DL (2002) A network approach to dementia diagnosis and management. *ISCA Computer Applications in Industry and Engineering* 15:225–228
- Cohen ME, Hudson DL, Anderson MF, Deedwania PC (1994) A conjecture to the solution of the continuous logistic equation. *Int J Uncertain Fuzziness Knowl-Based Syst* 2(4):445–461
- Szego G (1939) *Orthogonal polynomials*, vol 59. American Mathematical Society, Providence
- Hudson DL, Cohen ME (2009) Diagnostic models based on personalized analysis of trends (PAT). *IEEE Trans Inf Technol Biomed*. doi:10.1109/TITB.2009.2031640
- Lyketsos CG, Roques C, Hovanec L, Jones BN (2001) Telemedicine use and reduction of psychiatric admissions from a long-term care facility. *J Ger Psych Neuro* 14(2):76–79
- Alisky JM (2006) Integrated electronic monitoring systems could revolutionize care for patients with cognitive impairment. *Med Hypotheses* 66(6):1161–1164
- Man DW, Tam SF, Hui-Chan CW (2003) Learning to live independently with expert systems in memory rehabilitation. *NeuroRehabilitation* 18(1):21–29
- Czaja SJ, Ruvert MP (2002) Telecommunications technology as an aid to family caregivers of persons with dementia. *Psychosom Med* 64(2):469–476
- Mundt JC, Kaplan DA, Greist JH (2001) Meeting the need for public education about dementia. *Alzheimer Dis Assoc Disord* 15(1):26–30
- Madan S, Bodagh IY (2002) Dedicated to the elderly: geriatric medicine on the internet. *Age Ageing* 31(1):70–74
- Wright LK, Bennet G, Gramling L (1998) Telecommunications interventions for caregivers of elders with dementia. *Adv Nurs Sci* 20(3):76–88
- Folstein MF, Folstein SE, McHugh PR (1975) Mini-mental state: a practical method for grading the cognitive state of patients for the clinician. *J Psychiatr Res* 12:189–198
- Blessed G, Tomlinson BE, Roth M (1988) Blessed-Roth Dementia Scale (DS). *Psychopharmacol Bull* 24(4):705–708
- Lawton MP, Brody EM (1969) Assessment of older people: self-maintaining & instrumental activities of daily living. *Gerontologis* 9(3):179–186
- Hudson DL (2009) *Knowledge-based systems: Wiley Encyclopedia of Electrical Engineering*. Wiley, Hoboken
- Cohen ME, Hudson DL, Deedwania PC (1997) Combining ECG analysis with clinical parameters for diagnosis of heart failure. *IEEE Eng Med Biol* 19:50–53