Empathic Computing

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Abstract. Empathic computing is an emergent paradigm that enables a system to understand human states and feelings and to share this intimate information. The new paradigm is made possible by the convergence of affordable sensors, embedded processors and wireless ad-hoc networks. The power law for multi-resolution channels and mobile-stationary sensor webs is introduced to resolve the information avalanche problems. As empathic computing is sensor-rich computing, particular models such as semantic differential expressions and inverse physics are discussed. A case study of a wearable sensor network for detection of a falling event is presented. It is found that the location of the wearable sensor is sensitive to the results. From the machine learning algorithm, the accuracy reaches up to 90% from 21 simulated trials. Empathic computing is not limited to healthcare. It can also be applied to solve other everyday-life problems such as management of emails and stress.

1 Introduction

The function of aging is disability. Cataracts, Alzheimer and Osteoporosis, for example, are common symptoms of old age. The Impressionist painter Claude Monet is believed to have developed cataracts in later life, and the effect may be seen in his paintings. Tones in his later paintings became muddy; whites and greens became yellow [6,85]. Edgar Degas was almost blind for his last twenty years. He worked mostly in pastel with increasingly broad, free handling. Henri Matisse lost his mobility in his later years. He had to draw from his bed and let his assistant cut the paper. Like those painters, most senior citizens prefer to live in their own homes independently. Can a machine have empathy to understand human's feeling or states? What can an empathic artifact do for us at home?

For decades, computers have been viewed as apathetic machines that only accept or reject instructions. Whether an artifact can understand human's feeling or state is a paradox of empathy. René Descartes claims that thoughts, feelings, and experience are private and it is impossible for a machine to adequately understand or know the exact feelings of people. On the other hand, Ludwig Wittgenstein states that there is no way to prove that it is impossible to adequately imagine other people's feeling [44]. Alan Turing argues that machine intelligence can be tested by dialogs through a computer keyboard [53,73,79]. In our case, the Turing Test can be simplified as a *time-sharing test*, where empathic machines and humans coexist in a care-giving system with a time-sharing schedule. If a person receives care continuously, then we may call the system 'empathic'.

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Empathic computing emerges as a new paradigm that enables machines to know who, what, where, when and why, so that the machines can anticipate and respond to our needs gracefully. Empathic computing in this study is narrowed down to understand the ‘low-level’ subconscious feelings, such as pain, illness, depression or anomaly. Empathic computing is a combination of Artificial Intelligence (AI), network communication and human-computer interaction (HCI) within a practical context such as healthcare.

The AI program ELIZA is perhaps the first artifact that is capable to engage in an empathic conversation [80]. Based on simple keyword matching, the program appears to be a ‘good listener’ to psychiatric patients. This shows that a small program could generate pseudo-empathy at a certain degree. However, human feelings and states are more than just verbal communication. We watch, listen, taste, smell, touch and search. Warwick’s project Cyborg [83] is probably the most daring physical empathic artifact. The pioneer implanted an electrode array under his skin that interfaced directly into the nervous system. The signal was fed into a robot arm that mimicked the dynamics of Warwick's own arm. Furthermore, the researcher implanted a sensor array into his wife’s arm with the goal of creating a form of telepathy or empathy using Internet to communicate the signal remotely.

With the growing need for home health care, empathic computing attracts attention from many fields. Recent studies include designing a home for elderly people or people with disabilities [17]. Healthcare systems are looking for an easy and cost-effective way to collect and transmit data from a patient’s home. For example, a study [26] shows that the GSM wireless network used by most major cell phone companies was the best for sending data to hospitals from a patient’s home. Universities and corporations have launched labs to explore the healthy living environment, such as LiveNet [65,40], HomeNet [28], and Philips’ HomeLab [27]. Furthermore, Bodymedia has developed the armband wearable sensor [8,20] that tracks body temperature, galvanic skin response, heat flux, and other data. The data are then uploaded to a special web site for food and nutrition advices.

In this paper, we explore concepts of empathic sensor webs and related empathic computing methods. As a case study, we focus on the wearable sensor network for anomalous event detection at home. Using a simple distributed wireless sensor network and an equally simple algorithm, we are able to determine if the person is in trouble in real time. They may have fallen over and hurt themselves; their body temperature may be abnormal; or they may have stopped moving for an extended period of time. It would be valuable to alert the appropriate persons for assistance.

2 Empathic Sensor Web

Alarm pheromones are released by insects such as fish and bees when they alert others of danger [61,42,88]. Although human alarm pheromones are still debatable, there is no doubt that our instinct often makes us aware of dangerous situations. People can usually sense trouble with a car from noises, vibrations, or smells. An experienced driver can even tell where the problem is. Empathic computing aims to detect anomalous events from seemly disconnected ambient data that we take for granted. For example, the human body is a rich ambient data source: temperature, pulses, gestures, sound, forces, moisture, et al. Also, many electronic devices provide pervasive ambient data streams, such as mobile phones, surveillance cameras, satellite images, personal data assistants, wireless networks and so on. The peripheral vision of the redundant information enables *empathic sensor webs*.

Early sensor webs were developed for environmental monitoring [19]. For example, the geographical information system developed by Jet Proportion Laboratory provides a pervasive, continuous, embedded monitoring presence. The concept is to deploy a large number of affordable heterogeneous sensors to form a macro instrument. The growing online sensors and mobile computing enable the sensor-rich Internet for serendipitous empathic systems. Unlike traditional sensor networks, empathic sensor webs have unique characteristics: affordability and interaction. In the following sections, we will discuss these in detail.

2.1 Serendipitous Sensors

Mass-produced electronic devices such as cable television sets and mobile phones provide affordable platforms for *ad-hoc* sensing and communication at a low cost. This is in contrast to the traditional sensor networks, which were mainly developed in government-sponsored institutes, large corporations or the military, where the market scale is very limited. Many commercial off-the-shelf devices can be used as sensors for empathic webs. For example, a webcam can be used for monitoring the elderly when they are at home alone [48]. A mobile phone can also be a diagnostic tool. As the sounds generated by breathing in asthma patients are widely accepted as an indicator of disease activity [63,49], researchers have investigated the use of a mobile phone and electronic signal transfer by e-mail and voice mail to study tracheal breath sounds in individuals with normal lung function and patients with asthma [5]. The results suggest that mobile phone recordings clearly discriminate tracheal breath sounds in asthma patients and could be a non-invasive method of monitoring airway diseases.

For over two thousand years, physical inspection has been a unique and important diagnostic method of Traditional Chinese Medicine (TCM). Observing abnormal changes in the tongue, blood volume pulse patterns, breath smells, gestures, etc., can aid in diagnosing diseases [94]. TCM diagnosis is a black-box approach that involves only input and output data around the body. For many years, scientists have been trying to use modern technologies to unleash the ancient knowledge base. For example, the computer-based arterial blood-volume pulse analyzer is a ‘rediscovery’ of the diagnostic method originated from ancient TCM [24].

Visual inspection of the tongue has been a unique and important diagnostic method of Traditional Chinese Medicine (TCM) for thousands of years. Observing the abnormal changes in the tongue proper and in the tongue coating can aid in diagnosing diseases [56]. The inspection of the tongue comprises the inspection of the tongue body and the coating. The tongue body refers to the tissue of the muscle and blood vessels, while the coating refers to something on the tongue like mosses, which are formed, according to the theory of TCM, by the rising of the ‘qi’ (energy) of the spleen and stomach. In the study [10], the author uses a portable digital scanner to acquire the tongue image. The features on the tongue are represented as a vector of variables such as color space coordinates L*a*b, texture energy, entropy and fractal index, as well as crack index. With Probability Neural Network, the model reveals the correlation between the colon polyps and the features on the tongue. Although the study is preliminary, it shows the potential of inexpensive mobile cameras playing a role in healthcare. TCM diagnos is is not a replacement of the modern diagnostic technologies such as MRI, CT, Ultrasound, DNA, but an alternative tool for early warning that brings people for further clinical diagnoses. With the growing digital technologies, it is possible to see more personal diagnostic tools in stores, just like those pregnancy test kits or diabetes self-test kits today.

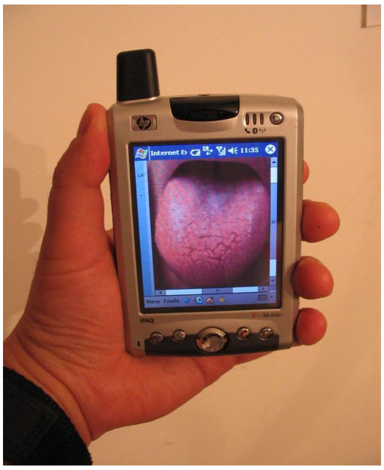

Fig. 1. Pocket PC-based tongue imaging system

Many existing information systems may also be used as empathic sensor webs. A wireless local network, for example, can provide a serendipitous user positioning system. Based on the Radio Signal Strength Indication (RSSI) in an indoor wireless environment, the system can estimate the distance between the access point and the wireless device. The triangulation of the user's location can be calculated from multiple access points. However, in many cases, only one access point is actively connected. Indoor furniture information and the Bayesian model are used to improve positioning accuracy with physical constraints and historical ground truth data. Figure 2 shows a screen capture of the wireless laptop positioning output. With mobile sensors such as RFID (Radio Frequency Identification) tags and multiple readers, a positioning system can also be configured in addition to the WiFi (Wireless Fidelity) system. Combined with multi-modal sensors, such as RFID, sound, infrared and magnetic signals, the positioning accuracy can be further improved.

The widely distributed open sensory system also raises serious concerns about data privacy [69]. Figure 2 shows an output from a wireless device positioning system at a building, where the location of wireless users and access points are visible on the Internet. The identity of users is replaced with a dot to preserve individual privacy.

2.2 Interacting with Sensor Web

For many years, sensor networks have often referred to the networked stationary sensors that are embedded inside the infrastructure systems. For example, surveillance cameras,

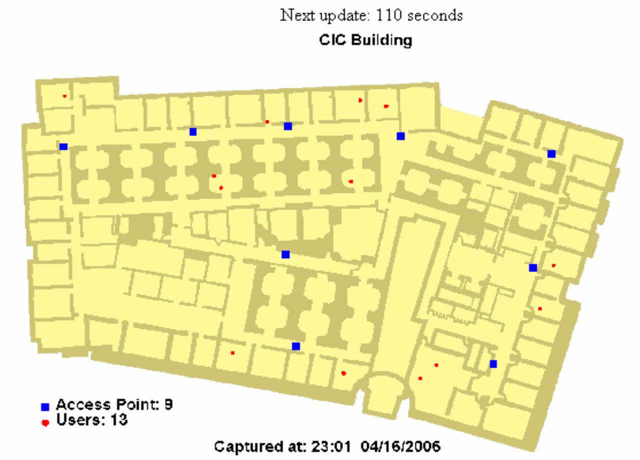

Fig. 2. Screen capture of the real-time wireless positioning system

WiFi access points, RFID readers, smart carpets, IR motion sensors, proxy sensors and so on. Stationary sensors are normally ubiquitous and fast in communication. However, they have dead zones and poor scalability. For example, for house monitoring, the more rooms in a house, the more cameras are needed. Consequently, the cost of a sensor network in a home would grow exponentially as rooms increase.

To solve the scalability problem, one solution is to enable mobile sensors interacting with stationary sensor networks. Mobile sensors include wearable or portable sensors, such as implanted RFIDs, mobile phones, e-watches, armband sensors, smart shoes or smart clothes. Mobile sensors can be configured as ad-hoc sensor networks by themselves, e.g. ZigBee ad-hoc network. These sensors are intrusive, but have a good spatial and temporal scalability if the number of people is small.

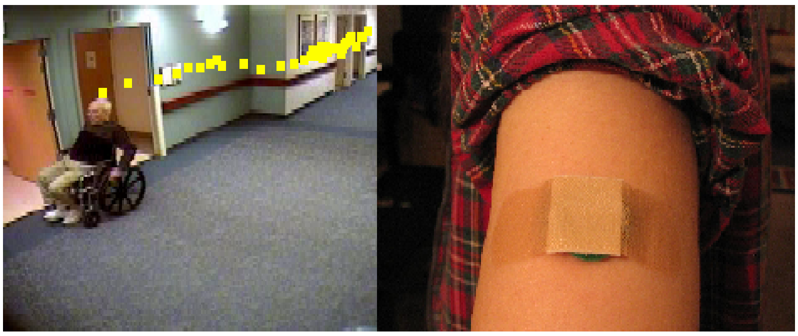

Fig. 3. A camera view of a nursing home with an overlay of a trajectory of the tracked human head positions (stationary sensor, left) and a prototype of the wearable infrared, temperature and motion sensors (mobile sensor, right)

2.3 Power Law of Resolution

A growing number and variety of sensors and other data sources are generating ever-larger volumes of data, including text, numeric, geospatial, and video data. Sensor webs would bring an 'information avalanche' to us that may overwhelm our data interpreting systems. The Radio Frequency Identification system is a vivid example. A large number of RFID across checkpoints in a supermarket may jam the network and computer systems. Distributed or localized data processing is necessary for sensor webs for the manageable network traffic control and computing resources. We must minimize the information flow while maximizing the perceptual capacity in a sensor web. Fortunately, the most important advantage of a sensor web is its interactivity. Multiple low-resolution sensors online may generate high valued results.

The fidelity of a sensor web can be distributed as a power law, or Pareto curve. Thus, we have about 80% low resolution and 20% high resolution. Human information processing follows the power law. If the data are plotted with the axes being logarithmic, the points would be close to a single straight line. Humans process only a very small amount of information in high fidelity, but large amounts of information in middle or low fidelity. The amount of processed information is roughly inversely proportional to its level of fidelity. Therefore, we have a fidelity power law for assigning the information processing capability for sensory channels. Given the amount of sensory information X, and the processing fidelity Y, the relation can be expressed as:

$$Y = -\, a \cdot log(X) + b \tag{1}$$

where a and b are the constants. For example, we have surprisingly low visual acuity in peripheral vision (rods) but very high visual acuity in the center of gaze (cones). Curiously, despite the vitality of cones to our vision, we have 125 million rods and only 6 million cones. Our gaze vision is optimized for fine details, and our peripheral vision is optimized for coarser information.

Because network capacities are limited in comparison with those of wired networks, wireless networks are much more susceptible to overload if the wrong data is transmitted or is sent to the wrong people at the wrong time. Sending video to someone who does not want or need it not only distracts the human, but also uses up network bandwidth that cannot be used for something more useful. One approach is content routing, which attempts to move data to where it is needed for analysis or decision making without overloading wireless links. Another strategy is to anticipate the locations where many people will need to look at a particular piece of information, and then move that information to a local server for later asynchronous access.

Considering a remote sensing system for monitoring a community of elderly people, how many screens do we need for the control room? How many operators do we need for vigilance around the clock? In author's recent study [11], eye gaze tracking and face detection technologies are applied to optimize the throughput of a wireless mobile video network. From the empirical experiments it is found that multiple resolution screen switching can reduce the network traffic about 39%. With eye gazing interface, the throughput of the network reduced about 75%. Combining the eye tracking and face detection in the video, the overall throughput reduction reaches about 88%.

3 Sensor-Rich Computing

Empathic sensor webs bring a new paradigm of *sensor-rich computing* that does more distributed measurements than centralized computing, which exists in nature for millions of years. For example, a modern aircraft requires about 6 million lines of code to be aware of its situations, based on a few sensors. On the other hand, a fly uses only a few hundred neurons in its brain (about 2 percent) to do the same job. About 98% of the neurons the fly uses are devoted to process near one million channels of sensory data [93]. In light of this, we could use more distributed sensors to replace the heavy-duty centralized computing. This also suggests that there is no need for high-resolution sensors. Instead, a large number of coarse-grained sensors could give reasonable results. Most biosensors are transformers that convert one kind of signals into another. A crock ranch can feel human motion by sensing the airflow that passes its hairs. Obviously, it is not capable to solve the complex fluid dynamics equations [54].

An ad-hoc sensor web may generate more data than we can handle. Most information today hasn't been analyzed even if it actually contains actionable information. Automation is essential to process, filter, and correct this flood of data, and to present it as accurate and actionable information for humans. As information from multiple sources flows up to higher levels, a more complete picture can be created, enabling adjudication at the higher level to correct erroneous information that has arisen at lower levels. Adjudication also helps reduce the volume of information being pushed up, which can overwhelm decision-makers.

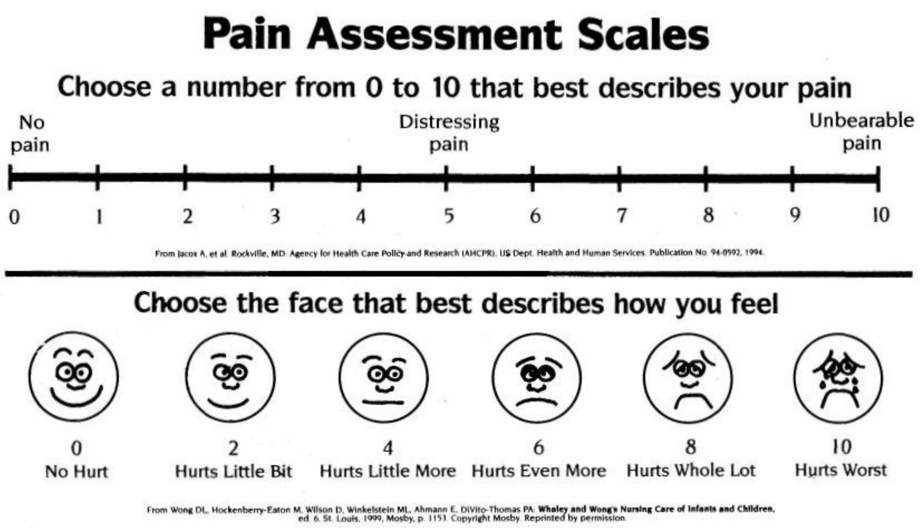

Fig. 4. Expressions of pain in pictures, numbers and words[1]

[1] From Hockenberry MJ, Wilson D, Winkelstein ML: Wong's Essentials of Pediatric Nursing, ed. 7, St. Louis, 2005, p. 1259. Used with permission. Copyright, Mosby.

3.1 Semantic Differential Representation

The Semantic Differential method measures perceptual and cognitive states in numbers or words. For example, the feeling of pain can be expressed with adjectives, ranging from weakest to strongest. Figure 4 shows a chart of visual, numerical and verbal expressions of pain in hospitals: No Hurt (0), Hurts Little Bit (2), Hurts Little More (4), Hurts Even More (6), Hurts Whole Lot (8) and Hurts Worst (10).

The physical feeling can be quantified with mathematical models. When the change of stimulus (*I*) is very small, we won't detect the change. The minimal difference (ΔI) that is just noticeable is called perceptual threshold and it depends on the initial stimulus strength I. At a broad range, the normalized perceptual threshold is a constant, $\Delta I/I = K$. This is so-called Weber's Law [39].

Given the perceptual strength E, as the stimulus I changes ΔI, the change of E is ΔE. We have the relationship $\Delta E = K*\Delta I/I$. Let ΔI be dI and ΔE be dE, thus we have the so-called Weber-Fechner's Law:

$$E = K*ln(I) + C \tag{2}$$

where, C is constant and K is Weber Ratio, I is stimulus strength and E is the perceptual strength. Weber-Fechner's Law states that the relationship between our perceptual strength and stimulus strength is a logarithm function. Studies show the values of Weber Ratios: sound strength 0.088, sound pitch 0.003, pressure 0.136, and illumination 0.016 [39].

3.2 Inverse Physics

Inversion is the process of retrieving physical properties [**P**] from observations [$\mathbf{P} = f^{-1}(\mathbf{O})$]. For example, for given vibration, sound and infrared signals, the state of people in a room can be estimated from physical models [$\mathbf{B} = f(\mathbf{W})$]. The simplest inversion to retrieve human state W from observation **B** [$W = f^{-1}(\mathbf{B})$] is a linear regression

$$W = C_1B_{1,h} + C_2B_{1,v} + C_3B_{2,h} + ... \tag{3}$$

For given physical properties, we can generate a library of high resolution simulation results for sensors. Most inverse problems are *nonlinear* in nature [74]. The generalized nonlinear regression (GNR), a machine learning model [29], can be used to estimate the human states from observations:

$$W(\vec{B}) = \sum_{i=1}^{N} \hat{W}_i D_i \Big/ \sum_{i=1}^{N} D_i \tag{4}$$

$$D_i = \exp[-\sum_{j=1}^{M} \frac{(\hat{B}_{j,i} - B_j)^2}{(\rho_i \sigma_i)^2} \tag{5}$$

where $\hat{W}_i$ and $\hat{B}_{ji}$ are human states and observations from forward model simulations and previous retrieval results. ρ is a correlation factor between observation channels, and σ is measurement error of $\hat{B}_j$. Based on radial-bases neural networks, GNR is a non-parametric estimation method. Retrievals using GNR are as straightforward as linear regressions, but yield more accurate results. GNR has been tested in many remote sensing applications. With all the existing simulation models, we can produce equivalent $\hat{W}_i$ and $\hat{B}_{ji}$ for interested events from forward simulation. Comparing with other inverse methods, GNR is more universal since it does not require *a priori* information. However, GNR is not necessarily an ideal candidate for embedded sensor fusion due to its large memory demand. To improve the parallelism of the algorithm, we modify the GNR to its subset, the Koheren Model [33,34], or Radial Basis Function (RBF) model, which is simpler and easier to be embedded and parallelism.

$$W(\vec{B}) = W_0 + \sum_{i=1}^{k} \hat{W}_i D_i \tag{6}$$

$$D_i = \exp[\frac{dist(\hat{B}_i, \vec{B})^2}{2\sigma_u^2}] \tag{7}$$

where each $\hat{B}_i$ is a kernel center and where $dist()$ is a Euclidean distance calculation. The kernel function D_i is defined so that it decreases as the distance between B_u and B_i increases. Here k is a user-defined constant that specifies the number of kernel functions to be included. The Gaussian function D_i is centered at the point $\hat{B}_i$ with some variance σ_u^2. The function provides a global approximation to the target function, represented by a linear combination of many local kernel functions. The value for any given kernel function is non-negligible only when the input $\vec{B}$ falls into the region defined by its particular center and width. Thus, the network can be viewed as a smooth linear combination of many local approximations to the target function. The key advantage of RBF networks is that they contain only summation of kernel functions, rather than compounded calculation, so that RBF networks are easier to be parallelized. In addition, RBF networks can be trained with a matrix of weights so that they need less memory than GNR that stores a sequence of historical data.

3.3 Inversion-On-Chip

Sending raw data to a server would saturate the bandwidth of a sensor web. To solve the problem, we have also implemented the above algorithms on the Field Programmable Gate Array (FPGA), which is reconfigurable and parallel [89]. Inversion-on-chip enables us to offload the data traffic from the sensor web and synthesize the alarm pheromones in real-time. A prototype of the physical inversion models is constructed on the NI PXI-7831R FPGA prototyping board. The FPGA Vertex II 1000 contains 11,520 logic cells, 720 Kbits Block RAM, and 40 embedded 18x18 multipliers. Figure 5 shows a basic design for GNR on FPGA.

To increase the capacity and speed, we have also implemented Radial Basis Function, a subset of the Generalized Non-linear Regression model. The RBF model increased the capacity in two folders and up.

We have the following preliminary results through our benchmark experiments: 1) the FPGA chip over-performance Pentium at least two to three orders of magnitude in

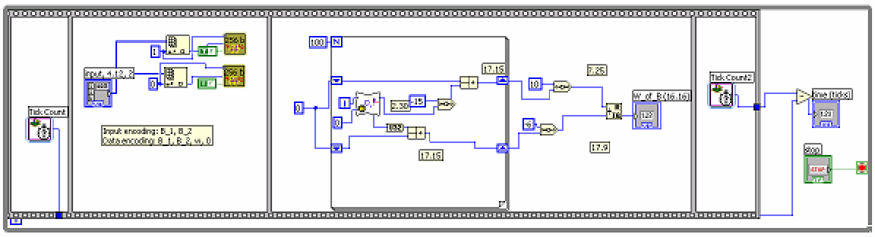

Fig. 5. Basic design for GNR implementation on FPGA

terms of speed. For example, for the GNR model, the FPGA uses 39 µs with 10 MHz clock speed. Pentium uses between 1000 µs and 2000 µs with 1 GHz clock speed. 2) The fixed point Radial Basis Function algorithm demonstrated ideal parallelism as the number of simultaneous basis compares increases. Figure 6 shows the computing time for the parallel processing for GNR and RBF models (left) and the resources utilization by the two models (right).

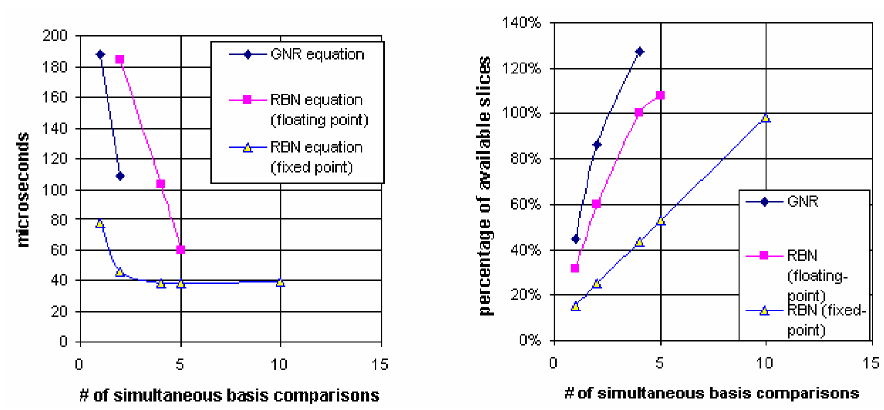

Fig. 6. Computing Time (left, 2 Inputs and 100 Basis) and Resources Utilization (right)

4 Anomaly Detection – Case Study

Detecting elderly people's health states at home has been an increasing demand. There are many solutions for detecting a fall, such as passive sensor networks and active sensory networks. In our trials with wireless sensor networks, we were using a MICA2/DOT development platform [16]. These sensors are easy to set up and are able to sense temperature, x and y position, light, sound, and x and y acceleration. These nodes are compatible with TinyOS. This is an open source platform for node programming. Our initial setup is very humble: one base station connected to a computer, and one node attached to the subject (Figure 7).

This, of course, can be extended to include multiple nodes all over the body as well as all over the house. By using these tiny sensors, our goal is to determine, in the most accurate and non-intrusive way possible, if someone has fallen down. Our algorithm must be able to process data quickly, and to distinguish a fall from other daily activities such as sitting or lying down, bending over, etc. This simple test is to show that wireless sensor networks can be used reliably to send data back to a hospital or care-giver.

4.1 Sampling Rate and Sensor Placement

When choosing a sampling rate for the sensor, we need to determine how fast a person falls and also how fast the sensor could reliably send data back to the base node. In the beginning, our sensor's sampling rate was at four seconds. With this slow sampling rate, one could see that the person was standing, and then fallen, but it was hard to find where the initial fall was. We increased the sampling rate to four times per second and then we were able to see the change as the person fell. Four times per second was chosen because it gives enough data to determine a fall, but it is slow enough so that more sensors could be added and the network would not slow down.

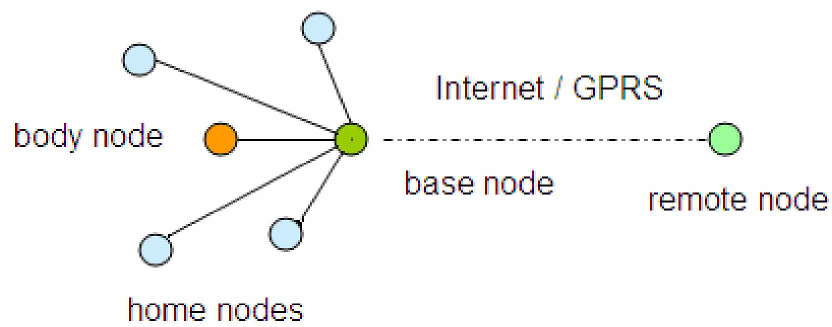

Fig. 7. The sensor web test bed

Fig. 8. Example of node placed on body

The position of the sensor was another factor that was very important. Our goal is to make the sensor invisible to the user, yet still very functional. As you will see, we tried several different locations including the knee, the belt, the shoulder, and the forehead. When the sensor was placed on different parts of the body, it would give very different readings due to the different movements of the particular body part. We wanted to pick the part of the body that gave us the cleanest readings and that was also easy for the user to wear. The belt and the forehead gave us the best readings. We decided that the belt would be more realistic for a person to wear all the time than the forehead.

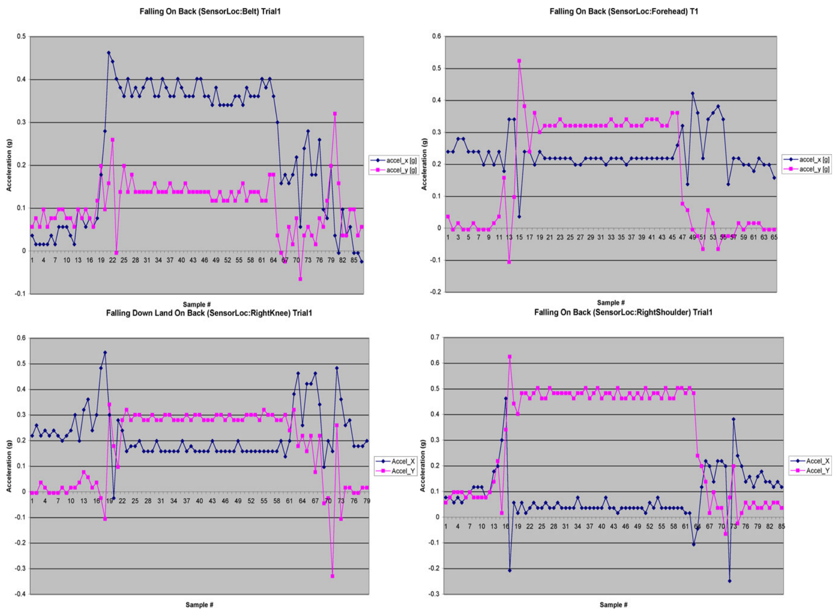

Fig. 9. Differences in fall when sensor was placed on different parts of the body. Starting at the top left and going clockwise we have sample fall data from belt, forehead, right shoulder, right knee.

4.2 Empirical Studies

In our design, we set up the system to log all the data received from the nodes into a SQL compliant database. We did this for a few reasons. First of all, the data is kept in a place that can be easily accessed by programs or hospitals that need to check all data to see if there are changes over time in various areas. Another reason is that if all the data is in a database, the programs can be set up to run from anywhere in the world as long as they have Internet access. This means that the programs could be run from a hospital or a caretaker's home and that would make reporting anomalous behavior easier. Using TinyOS, we were able to set up a program that simply reads data packets received from the nodes, parses them into relevant data, and logs them into an SQL database for us to a defined format. We had this program running all the time in order to log the data. Once we had the data, we had to determine a way to analyze it that was both fast and accurate.

The sensor was given readings at a rate of four per second. This could be increased or decreased depending on the application. We found four readings per second to be sufficient for fall detection. When we are talking about an always on, always reporting sensor, the data can get overwhelming very quickly. For this reason we must choose an algorithm that is fast and efficient as well.

Fig. 10. Lab environment for simulated falls

When a person falls, the body orientation changes from vertical to horizontal. This causes the *x* and *y* acceleration to switch values and is a very good indicator that someone has fallen down. When the sensor is placed on the belt, there are very few times that a person changes XY-orientation at that speed. So we developed and trained a system of neural networks that looked for drastic changes in the XY-orientation or the subject. The neural network is a two-layer feed forward network with ten inputs and one output. Each node in the hidden layer uses the kernal function and the output uses a simple linear transfer function. The neural network was trained using the neural network stated in equation 6 and 7. This modal was used because of its relative speed and accuracy.

We then trained each modal using two walking samples, two falling samples, two have fallen samples, and two getting up samples, for a total of eight training samples for the neural network. We intend to develop a way to keep analyzing data as it comes into the database, as well as to compare it to previous data. We set up a window of ten measurements at a time. As soon as a new signal came in, we put all ten values through our series of neural networks and read the results. If the resulting value that came out of our neural networks is above a certain threshold, we would count that as a *fall*. Once a person has fallen, they cannot fall again, yet the data would continue to indicate that they had fallen until they had gotten up. This problem was easily solved with the inclusion of a flag that was set when someone fell, and reset when they got up. As long as the flag was set, they could not fall again until it was reset.

4.3 Detection Results

We tested our algorithm with data received from placing the node on different parts of the body. We placed the node on the forehead, the right shoulder, the belt, and the knee. Then we tested falling onto different sides of the body (chest, back, left side, right side) as well as everyday activities such as walking, sitting, and standing. We simply needed a way to determine if our method would detect everyday movement and treat it as falls. We were able to determine a fall with the most accuracy when using the data from the node placed on the belt. In second place was placing the sensor on the forehead. This is most likely because the torso or the forehead of a person stays much more stationary as opposed to the knee or the shoulder. When the sensor was placed on the belt, we were able to determine a fall almost every time. Our results are summarized in Table 1.

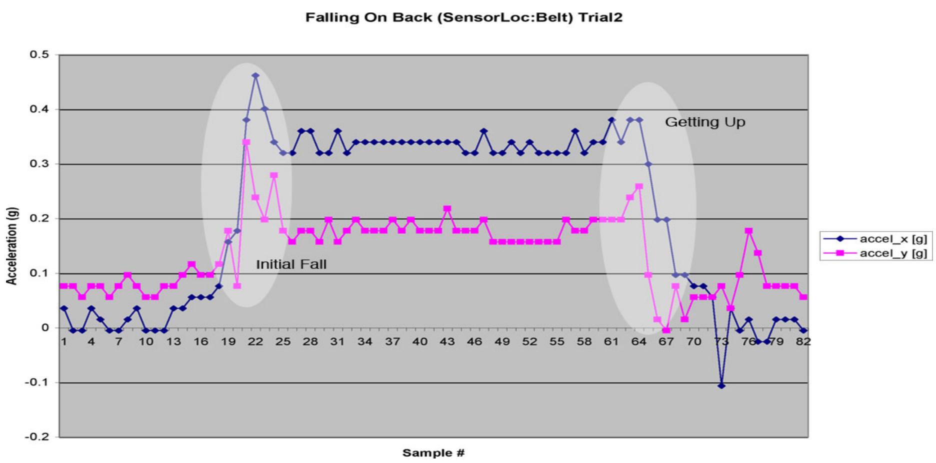

Fig. 11. Example of data received from a fall. The point where the person fell is indicated.

Table 1. Results of detecting the fall

Sensor Position	Identified Correctly	Identified Incorrectly	Missed	Total Trials
Belt	90%	5%	5%	21
Forehead	81%	14%	5%	21
Right Shoulder	71%	19%	10%	21
Right Knee	62%	29%	9%	21

The model developed in this study is not enough for detecting all the conditions. Diabetes patients, for example, often collapse slowly when the blood sugar is low. In this case, a combination of motion sensors with other sensors or interfaces would be desirable, such as a digital watch that sends a beep to the user after detecting a motionless event. The user would push a button if everything was OK. Otherwise, the wearable device will send the alarm to the network after a few inquiries.

5 Conclusions

Empathic computing aims to enable a computer to understand human states and feelings and to share the information across networks. Empathic sensor webs provide new opportunities to detect anomalous events and gather vital information in daily life. The widespread availability and affordability makes it easier and cheaper to link already deployed sensors such as video cameras. New sensor web capabilities can have a major impact by changing how information is used in homecare. For example, smart mirror for tongue inspection, smart room and wearable sensors for motion pattern analysis, etc.

Empathic computing brings a new paradigm to the network-centric computing, which focuses on sensor fusion and human-computer interaction. The author addresses the potential information avalanches in the empathic sensor web and proposes possible solutions for information reduction at the source side, for instance, applying the power law for multi-resolution channel design and interacting mobile sensors with stationary sensors. Ultimately, empathic computing is sensor-rich computing. In this paper, semantic differential expressions are discussed. They can be used to transform human feelings into digital forms, or vice versa. Inverse Physics methods are introduced to model the human physical states.

As a case study in this paper, the author introduces a rapid prototype of the wearable empathic computing system that is to detect the fall event. It is not a complete system. Rather, it only shows how complicated an empathic computing could be involved. From the initial results, it is found that the location of the wearable sensor makes a difference. The belt, for example, is probably the most appropriate place to put the sensor for detecting a fall. From the machine learning algorithm, the accuracy reaches up to 90% from 21 simulated trials.

The empathic sensor web concept fits into a larger picture of a smart house [12,15,17]. Wireless sensors can be placed almost anywhere and give readings about what is happening in the home. The possibilities of wireless sensor networks in the home are infinite. In addition to being unwired, wireless communications are highly and dynamically reconfigurable without physical linking, which allows the reconfiguration of communications infrastructure in real-time. Its dynamic nature makes wireless communication especially suitable for reaching areas not served well by fixed infrastructure, as well as places where the fixed infrastructure has been compromised or damaged.

Empathic computing is not limited to helping the aging society. It can be applied to solve other everyday-life problems, e.g. the empathic computing tool would remind users to take regular breaks by monitoring online duration and stress level.

The final deployment of an empathic sensor web may rely not only on technical, but also on economical and human factors. The willingness to cooperate and a willingness to make changes are critical.

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References

[1] Aarts, E and Marzano, S. The new everyday: views on Ambient Intelligence, 010 Publishers Rotterdam; 2003

[2] Akgul, Y.S., et at.: Automatic Extraction and Tracking of the Tongue Contours. IEEE Trans. on Medical Imaging. Vol.18, No.10, October, 1999

[3] Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E.: Wireless Sensor Networks: A Survey (2001)

[4] Albowicz, Joe, Chen, Alvin, Zhang, Lixia: Recursive Position Estimation in Sensor Networks. UCLA Internet Research Laboratory.

[5] Anderson, K., Qiu, Y., Whittaker, A.R., Lucas, Margaret: Breath sounds, asthma, and the mobile phone. Lancet. 358:1343-44. (2001)

[6] Backhaus, W., Kliegle, R. and Werner, J. (eds): Color Vision, Walter de Gruyter, Berlin, New York, 1998

[7] Biship, Christopher M.: Neural Networks for Pattern Recognition. Oxford: Oxford UP, 1995.

[8] Bodymedia: www.bodymedia.com

[9] Bossert, W. H. (1963): Chemical communication among animals. Recent Progress in Hormone Research 19, 673-716.

[10] Cai, Y et al, : Ambient Diagnostics, in Y. Cai (ed.) Ambient Intelligence for Scientific Discovery, LNAI 3345, pp. 248-262, 2005

[11] Cai, Y. and Milcent, G.: Video-On-Demand Network Throughput Control, Proceedings of Ambient Intelligence for Everyday Life, San Sebastian, Spain, July, 2005

[12] Chan, M., Hariton, C., Ringeard, P., Campo, E.: Smart House Automation System for the Elderly and the Disabled. Systems, Man and Cybernetics, 1995. 'Intelligent Systems for the 21st Century'., IEEE International Conference.

[13] Chaney, G.R.: Do you Snore? http://www.garnetchaney.com/help for snoring.shtml

[14] Chen, S., Cowan, C.F.N., and Grant, P.M.: Orthogonal least squares learning algorithm for radial basis function networks. IEEE Transactions on Neural Networks, Vol.2, no.2, March. (1991) 302-309

[15] Chong, Chee-Yee, and Kumar, Srikanta P.: Sensor Networks: Evolution, Opportunity, an Challenges (2003)

[16] Crossbow: MOTE-KIT 5x4x. 2005. Crossbow Technology Inc.

[17] Dewsburry, Guy, Taylor, Bruce, Edge, Martin: Designing Safe Smart Home Systems for Vulnerable People.

[18] ELIZA demo: http://www-ai.ijs.si/cgi-bin/eliza/eliza_script

[19] Environmental Studies with the Sensor Web: Principles and Practice, by Kevin A. Delin, Shannon P. Jackson, David W. Johnson, Scott C. Burleigh, Richard R. Woodrow, J. Michael McAuley, James M. Dohm, Felipe Ip, Ty P.A. Ferré, Dale F. Rucker, and Victor R. Baker, Sensors, Vol. 5, 2005, pp. 103-117

[20] Farringdon, Jonathan, and Sarah Nashold: Continuous Body Monitoring. Ambient Intelligence for Scientific Discovery (2005): 202-223.

[21] Figueiredo, M, et al: Expanding NASA's Data Processing to Spacecraft, Computer, June, 1999

[22] Galstyan, A.: Distributed online Localization in sensor networks using a moving target. University of Southern California. 2004

[23] Gist, Y. J., and Lisa I. Hetzel. Department of Commerce: We are the People: Aging in the United States. N.p.: n.p., 2004.

[24] Gunarathne, G.P. Presmasiri, Gunarathne, Tharaka R.: Arterial Blood-Volume Pulse Analyser. IEEE, Instrumentation and Measurement Technology Conference, AK, USA, May. (2002) 1249-1254
[25] Hayes, P.J. and Ford, K.M. (1995): Turing Test Considered Harmful, Proceedings of International Joint Conference on Artificial Intelligence (IJCAI-95), pp. 972-977, Montreal.
[26] Herzog, A., and Lind, L.: Network Solutions for Home Health Care Applications. Linkoping University (2003)
[27] HomeLab: http://www.research.philips.com/technologies/misc/homelab/
[28] HomeNet: http://homenet.hcii.cs.cmu.edu/
http://www.coe.berkeley.edu/labnotes/1101smartbuildings.html
http://www7.nationalacademies.org/cstb/wp_digitaldivide.pdf
[29] Hu, Y., B. Lin and Y. Cai: Determination of sea surface wind speed and temperature using TMI data: A General Regression Neural Network Approach. Submitted to Remote Sensing of Environment.
[30] Jang, J.H., Kim,J.E., Park,K.M., Park,S.O., Chang,Y.S., Kim,B.Y.: Development of the Digital Tongue Inspection System with Image Analysis. Proceedings of the Second Joint EMBS/BMES Conference. Houston, TX, USA. October 23-26. (2002)
[31] Kaiser, R.: Smart toilet a sure sign of future technology. Chicago Tribune. Saturday December 23. (2000)
[32] Kaiser, W J., and G J. Pottie.: Wireless Integrated Network Sensors. Communica-tion of the ACM May 2000: 51-58.
[33] Kohonen, T.: Self-organization and Associative Memory. 2nd edition, Springer, Berlin. (1988)
[34] Kohonen, Teuvo, Barna, Gyorgy, Chrisley, Ronald: Statistical Pattern Recognition with Neural Networks: Benchmarking Studies. Helsinki University of Technology.
[35] Lansing, F., L. Lemmerman, A. Walton, G. Bothwell, K. Bhasin and G. Prescott, 2002: Needs for Communication and Onboard Processing in the Vision Era. 2002 IGARSS conference proceeding.
[36] Legg, Gary. ZigBee: Wireless Technology for Low-Power Sensor Networks. 6 May 2004. TachOnLine.
[37] Lewin, M.E., and Altman, S., eds. America's Health Care Safety Net: Intact but Endangered, Institute of Medicine, 2000.
[38] Li, Q., Rosa, Michael De, Rus, Daniela: Distributed Algorithms for Guiding Navigation across a Sensor Network. Dartmouth Department of Computer Science (2003)
[39] Li, W.B.: Ergonomics for Interior and Furniture Design, China Forestry Press, 2001
[40] LiveNet: http://hd.media.mit.edu/livenet/
[41] Mainwaring, Alan, Polastre, Joseph, Szewczyk, Robert, Culler, David, Anderson, John: Wireless Sensor Networks for Habitat Monitoring. (2002).
[42] McClintock, M.K. (1984). Estrous synchrony: modulation of ovarian cycle length by female pheromones. Physiological Behavior 32, 701-705
[43] McDermott, M.M. et al: Functional Decline in Peripheral Arterial Disease: Associations With the Ankle Brachial Index and Leg Symptoms. JAMA, July. 292:453-461 (2004)
[44] McNabb, R.: The Paradox of Empathy, Philosophy Now, No.52, 2005
[45] Meribout M., Nakanishi M.; Ogura T., A parallel algorithm for real-time object recognition, Pattern Recognition, Sept. 2002, vol. 35, no. 9
[46] Michell, T.: Machine Learning, The McGraw-Hill Companies, 1997
[47] Moore, G.: Cramming more components onto integrated circuits. Electronics, Vol. 38, No. 8, April 19. (1965)
[48] Ordonez, J.: The Web Chat That Saved Mom's Life, Newsweek, November 28, 2005

[49] Pasterkamp, H., Kraman, S.,S., Wodicka, G.R.: Respiratory sounds: advances beyond the stethoscope. American Journal of Respiratory Critical Care Medicine. 156:974-87 (1997)
[50] Pathirana, P.N.: Node Localization using mobile robots in delay-tolerant sensor networks, July 2005
[51] Perrig, P., R. Szewczyk, J.D., T.V. Wen, D. E. Culler, SPINS: Security Protocols for Sensor Networks, Wireless Networks, Volume 8, Issue 5, Sep 2002, Pages 521 – 534
[52] Picton, P.: Neural Networks. 2nd edition, Palgrave, Basingstoke. (2000)
[53] Popple, A.V.: The Turing Test as a Scientific Experiment. Psychology, 7(15), 1996
[54] Rinberg, D. and Davidowitz, H. Do cockroaches 'know' about fluid dynamics? Nature 2000 Jul 27;406(6794):368
[55] Rodgers, C.D., Inverse Methods for Atmospheric Sounding, World Scientific. 2002.
[56] Schnorrenberger, C. and Schnorrenberger, B. Pocket Atlas of Tongue Diagnosis, Thieme, Stuttgart, New York, 2005
[57] Sensor Web at JPL: http://sensorwebs.jpl.nasa.gov/
[58] Shah, Rahul C., Rabaey, Jan M.: Energy Aware Routing for Low Energy Ad Hoc Sensor Networks. University of California Berkley 2002.
[59] Silverstrim, J.E, H. Eric W, C. Kent: Method and Apparatus for Multi-Waveform Wireless Sensor Network. Patent WO2004US33051 (5-12-2005).
[60] Sinha, Amit, Chandrakasan, Anantha: Dynamic Power Management in Wireless Sensor Networks. IEEE Design & Test of Computers pg 62-74 (2001)
[61] Smith, R.: Alarm signals in fishes. Rev Fish Biol Fish 2:33-63, 1992
[62] Spath, H.: Cluster analysis algorithms. Ellis Horwood Ltd., Chichester. (1980)
[63] Spiteri, M.A., Cook, D.G., Clarke, S.W.: Reliabilty of eliciting physical signs in examination of the chest. Lancet. 2:873-75. (1988)
[64] Starner, T.: Interview with Thad Starner, by Peter Thomas. New Scientist. http://www.media.mit.edu/wearables/lizzy/newsci.html (1995)
[65] Sung, M. and A. Pentland, MIThril LiveNet: Health and Lifestyle Networking, Workshop on Applications of Mobile Embedded Systems (WAMES'04) at Mobisys'04, Boston, MA, June, 2004
[66] Sung, M. and Pentland, A. Minimally-Invasive Physiological Sensing for Human-Aware Interfaces, HCI International 2005, HCII'05
[67] Sung, M., A. Pentland, Minimally-Invasive Physiological Sensing for Human-Aware Interfaces, HCI International 2005, (HCII'05)
[68] Sung, M., C. Marci, A. Pentland: Wearable Infrastructure and Sensing for Real-time clinical Feedback Systems for Rehabilitation, Journal of NeuroEngineering and Rehabilitation, (JNER'05)
[69] Tanz, O and Shaffer, J.: Wireless Local Area Network Positioning, in Y. Cai (ed.) Ambient Intelligence for Scientific Discovery, LNAI 3345, pp. 248-262, 2005
[70] Taylor, C.: Simultaneous Localization, Calibration, and Tracking in an ad Hoc Sensor Network.. MIT April 2005
[71] Tessier, R. et al: Reconfigurable Computing for digital signal processing: A survey, The Journal of VLSI Signal Processing, May, 2001, vol. 28, no. 1 and 2.
[72] Tredennick, N. Get ready for reconfigurable computing, Computer Design, pp 55-63, 1998.
[73] Turing, A.M.: Computing Machinery and Intelligence. Mind, 59: 433-460, 1950
[74] Vann, L. and Y. Hu: A Neural Network Inversion System for Atmospheric Remote-Sensing Measurements. 2002 IEEE IMTC.
[75] Wang, J. J.; Katz, R. B.: Plants, W. C., SRAM Based Re-Programmable FPGA for Space Applications. IEEE trans. on nuclear science, 1999, vol. 46, no. 6p1, pp. 1728

[76] Wasserman, P.D.: Advanced methods in neural computing. New York, Nostrand Reinhold. (1993)
[77] Watsuji, T., Arita, S., Shinohara, S., Kitade,T.: Medical Application of Fuzzy Theory to the Diagnostic System of Tongue Inspection in Traditional Chinese Medicine. IEEE International Fuzzy Systems Conference Proceedings. (1999) 145-148
[78] Watt, S.N.K.: Naive Psychology and the Inverted Turing Test. Psychology, 7(14), 1996
[79] Weizenbaum, J. Computer Power and Human Reason: From Judgment To Calculation, San Francisco: W. H. Freeman, 1976 ISBN 0-7167-0463-1
[80] Weizenbaum, J.: ELIZA - A Computer Program for the Study of Natural Language Communication between Man and Machine, Communications of the Association for Computing Machinery 9 (1966): 36-45.
[81] West, Brent W., Flikkema, Paul G., Sisk, Thomas, Koch, George W.: Wireless Sensor Networks for Dense Spatio-temporal Monitoring of the Environment: A Case for Integrated Circuit, System, and Network Design. Northern Arizona University.
[82] White paper of The National Academy of Sciences. Exploring the digital divide: Charting the terrain of technology access and opportunity.
[83] Wikipedia: Kevin Warwich, http://en.wikipedia.org/wiki/Kevin_Warwick
[84] Williams, J. A., Dawood, A. S. and Visser, S. J.: FPGA-Based Cloud Detection for Real-Time Onboard Remote Sensing, IEEE ICFPT 2002, Hong Kong
[85] Winston, R. (editor-in-chief): Human, DK Publishing, Inc. 2004
[86] Wu, H., Siegel, M. and Khosla,P.: Vehicle Sound Signature Recognition by Frequency Principle Component Analysis. The Proceedings of IMTC 1998 , selected in the IEEE Transaction on Instrumentation and Measurement Vol. 48, No. 5, ISSN 0018-9456. October. (1999) 1005-1009
[87] Wu, H., Siegel, M., Stiefelhagen, R., and Yang, J.: Sensor Fusion Using Dempster-Shafer Theory. The Proceedings of IMTC 2002. Anchorage, AK, USA, May 21-23.
[88] Wyatt, Tristram D. (2003). Pheromones and Animal Behaviour: Communication by Smell and Taste. Cambridge: Cambridge University Press. ISBN 0521485266.
[89] Xilinx Products, 2003
[90] Xu, L., et al.: Segmentation of skin cancer images. Image and Vision Computing 17. (1999) 65-74
[91] Yao, P.: Comparison of TCM Tongue Images with Gastroscopy Images. Shangdong S&T Publisher, ISBN 7-5331-1849-9. in Chinese. (1996)
[92] Yu, Zhanshou: Feed-Forward Neural Network. 2005.
[93] Zbibowski, R.: Fly like a fly, IEEE Spectrum, November, 2005
[94] Zhang, E.: Diagnostics of Traditional Chinese Medicine. Publishing House of Shanghai University of Traditional Chinese Medicine, ISBN 7-81010-125-0. in both Chinese and English. (1990)
[95] Zhao, Jerry, Govindan, Ramesh: Understanding Packet Delivery Performance In Dense Wireless Sensor Networks. University of Southern California Computer Science Department (2003)
[96] Zhou, X.S., Rui, Y., and Huang, T.S. (2003): Exploration of Visual Data, Kluwer Academic Publishers