Instinctive Computing

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Abstract. Instinctive computing is a computational simulation of biological and cognitive instincts. It is a meta-program of life, just like universal gravity in nature. It profoundly influences how we look, feel, think, and act. If we want a computer to be genuinely intelligent and to interact naturally with us, we must give computers the ability to recognize, understand, even *to have* primitive instincts. In this paper, we will review the recent work in this area, the building blocks for the instinctive operating system, and potential applications. The paper proposes a 'bottom-up' approach that is focused on human basic instincts: forage, vigilance, reproduction, intuition and learning. They are the machine codes in human operating systems, where high-level programs, such as social functions can override the low-level instinct. However, instinctive computing has been always a default operation. Instinctive computing is the foundation of Ambient Intelligence as well as Empathic Computing. It is an essential part of Human Computing.

1. Introduction

What is the fundamental difference between a machine and a living creature? *Instinct!* Instincts are the internal impulses, such as hunger and sexual urges, which lead humans to fulfill these needs. Freud [1] stated that these biologically based energies are the fundamental driving forces of our life. They act everyday to protect us from danger and keep us fit and healthy. However, we are often barely aware of them.

Perhaps the most striking things for us are hidden in our cells. Recent biological studies suggest that mammalian cells indeed possess more intelligence than we can imagine [2]. For example, the cell movement is not random. It is capable of immensely complex migration patterns that are responses to unforeseeable encounters. Cells can 'see', for example, they can map the directions of near-infrared light sources in their environment and direct their movements toward them. No such 'vision' is possible without a very sophisticated signal processing system [3].

Instinctive computing is a computational simulation of biological and cognitive instincts. It actually started fifty years ago. Norbert Weiner [97] studied computational models of Gestalt, self-reproduction and learning. According to him, these functions are a part of the holistic communication between humans, animals and machine, which he called it 'Cybernetics'. In parallel, John von Neumann proposed the cellular automata model to simulate self-reproduction [4]. The model constitutes finite state cells interacting with one another in a neighborhood within a two-dimensional space. The conceptual machine is far ahead of its time. Due to the limitations in hardware, people had forgotten the idea for several decades until the 1970's: Conway rediscovered it in his article "Game of Life" [5]. In the model, an organism has its instinctual states, birth, movement, eating and death. Interesting patterns emerge from cell interactions such as blooming, oscillation or extinction. Wolfram further proves that many simple cellular interactions can produce very complex patterns, including chaos. He argues that interactive algorithms are more important than the mathematical equations [7]. The spatial and temporal interaction among entities is the key to understanding their complexity. Today, computational cellular automata have become a powerful tool to reveal the natural human algorithms, from microscopic cellular morphology [8] to mass panic movement in subway stations [9].

Instinct is a meta-program of life, just like universal gravity in nature. It profoundly influences how we look, feel, think, and act. If we want a computer to be genuinely intelligent and to interact naturally with us, we must give computers the ability to recognize, understand, even *to have* primitive instincts. In this paper, we will review the recent work in this area, the architecture of an instinctive operating system, and potential applications.

2. The bottom-up approaches

The rapid progress of computer hardware development enables a bottom-up paradigm of computing: *embryonics* (embryonic electronics) [6]. The project BioWall is a bio-inspired hardware in size of 130 cubic feet, developed in the Swiss Federal Institute of Technology in Lausanne (EPFL). Scientists have investigated most of the possible avenues for novel computing, ranging from *phylogenetic* systems, inspired by the evolution of biological species, through *ontogenetic* systems, inspired by the development and growth of multicellular organisms, to *epigenetic* systems, inspired by the adaptation of individuals to the environment. FPGA (Field Programmable Gate Array) chips [10] were used to implement the cellular automata in the hardware. Thousands of FPGA chips were tiled together in a two-dimensional space like a wall. It is a reconfigurable parallel computer without a CPU (Center Processing Unit). This architecture allows the scientists to think outside of the box and develop novel bio-inspired software from the bottom of the thinking hardware: logic gates. Unfortunately, there is still no operating system for such a hardware implementation. Programming on this ad-hoc system could be very challenging.

Computer simulation of instinctive cognition has been studied in multiple disciplines. The computer model INTERACT mimics affective control from the viewpoint of dynamic interactionism, which combines psychological social psychological, system theory, linguistic, attitude measurement and mathematical modeling [11]. The computer model DAYDREAMER mimics the human daydreaming process and provides an empirical tool to study the subconscious programs embedded inside our mind [12].

Pentland coined the term 'Perceptual Intelligence' for the intelligence without words or logic [13]. He argues that if we can give computers the ability to perceive, classify and anticipate human interactions in a human-like manner, then the computer will be able to work with humans in a natural and commonsense manner. To understand and predict human behavior, the team has developed vision algorithms to augment faces, emotions and gestures. The work is then extended to the study of 'Human Dynamics' for a broader range of social interactions, such as mobile communication. This inspires a new wave of 'Human Computing' [104] studies. Instinctive Computing is an essential part of 'Human Computing'. It focuses on low-level functions and needs, similar to the machine code to software. While Human Computing algorithms attempt to answer questions such as, *who* the person is, *what* is communicated, *where* is the location, *when* did it happen, and *how* did the information get passed on. Instinctive Computing, on the other hand, attempts to answer the question of *why* someone behaves that way and predicts the consequences of one's behavior using commonsense.

Indeed *instinct is commonsense.* It has been an immense challenge to AI. For over 20 years, with over a 20-million-dollar investment, Lenat and his colleagues have been developing Cyc, a project that aims to create a reusable general knowledge base for intelligent assistants [14]. Cyc essentially is an ontological representation of human consensual knowledge, which can construct a semantic web where meaning is made explicit, allowing computers to process information intelligently. However, even Cyc has not touch the inner layers of human instincts.

Instinct often controls emotion. If we trace our anger, fear and, sadness back to its origin, we always can find the signatures of our instincts. The latest scientific findings indicate that emotions play an essential role in decision-making, perception, learning and action. They influence the very mechanisms of rational thinking. According to Picard [15], if we want computers to be genuinely intelligent and to interact naturally with us, we must give computers the ability to recognize, understand, even *to have* and express emotions. Minsky articulates emotion as a resource-intensive process [16]. In addition, he outlines a six-level model of mind from top to bottom: self-conscious reflection, self-reflection thinking, reflective thinking, deliberative thinking, learned reactions, and instinctive reactions. He elaborates the instinctive reactions are a set of "if-then" rules, which are primitive model of instinctive computing. According to Minsky, how to sort out the priority of such rules is quite a challenge.

Instinct has an impact on how we look at things. Researchers have studied Aesthetic Computing for understanding forms, functions, dynamics and values. Cohen seeks the answer to what are the minimal visual elements to be an interesting form [17]. He also ponders how to mix the paint color without perception. Leyton argues that shape is the memory storage [18]. By instinct, we use the imaginary symmetric structure to remember the shape process.

Instinct constitutes our social behaviors as well. Computational studies of human dynamics have been rapidly growing in recent decades. At the macroscopic level, the fundamental studies in social networks such as "the six degrees of separation" [19] and the "power law of the linked interactions" [20] shed lights on the scalability of human networking activities. Those remarkable models enrich our in-depth understanding of the dynamics in a very large network, which is a challenge to a visualization system. Spectrum-graph [21] is used to visualize human activities from ambient data sources such as gas stations and cellular phone towers. Graph models such as minimal graph cuts provide abstract, yet visual tools for analyzing the outliers in a very large social network [22]. Stochastic process based geographical profiling models have been developed to investigate serial killer's spatio-temporal patterns from the collected field data [23]. Furthermore, the cellular automata based panic model simulates the mass dynamics in public places such as train stations. The method computationally incorporates modeling, rules and visualization in one algorithm, which enables pattern discovery and rapid empirical experiments [24]. In a nutshell, the paradigm of the visual analytic social networks has been shifted from merely visual data rendering to model-based visual analysis. However, a single model may not be a panacea as many researchers have claimed. The adaptability and interactions between models and visual interfaces are perhaps potential solutions.

Computational visualization of human dynamics has been growing exponentially. Decades ago, human motion studies were largely dependent on the time-lapped photography, where joints were highlighted to form motion trajectories. Today, digital motion capturing and modeling systems enable the high fidelity modeling of the motion characteristics. Functional MRI (fMRI) systems visualize human nerve and cardiac dynamics in real-time, which has revolutionized the way of physiological and psychological studies such as driving [25]. Artificial Intelligence computational models also provide augmented cognition behaviors in navigation, planning and problem solving. A driver's eye gazing model [26], for example, is based on the classic ACT-R model [27]. The model mimics a human driver's visual experience in a rule-based system. However, as the developers of the system pointed out, how to incorporate the sensory interactions in the rule-based model is a challenge. Traditional AI models such as sequential and parallel processing have not been able to simulate the emergent behaviors.

3. Building blocks of Instinctive Computing

If we compare to our instinctive functions with a computer operating system, we would find some similarities: both are low-level programs (machine code). They intimately deal with physical devices; they operate autonomously as default. Their programs can be 'burned' into a ROM (Read-Only Memory). They can be overridden by high-level programs (applications). Besides, they all have very limited resources.

In this study, we view instinct as a metaphor for a future computer operating system, which includes the meta-programs for forage, vigilance, reproduction, intuition, and learning.

Forage is a basic urge for us to sustain life. Computational Swarm Intelligence [28] simulates ants' navigation process based on the trace of their pheromone. The algorithms have been widely adopted into network optimization applications, such as Traveling Salesman Problem, ad-hoc wireless mesh networking and network flow planning [28]. At the digital age, information foraging has become critical. The good news is that we can fetch valuable information with just a few mouse clicks. The bed news is that spyware or malware try to harvest sensitive data such as email addresses, personal identification numbers, birthdays and passwords, and documents. Bad interactions are real interactions. They contribute variety to a digital ecosystem, where novel algorithms emerge, for example, 'honey pots' and 'food-chains'.

Vigilance comes from our fears. A death instinct is universal to all creatures. Alarm pheromones are released by creatures such as fish and bees when they alert others of danger [29-31]. Although human alarm pheromones are still debatable, there is no doubt that our instinct often makes us aware of dangerous situations. Our tongue has evolved to have 5,000 taste buds - letting us know what to swallow, and what to spit out [32]. And we also have an instinctive reaction to things which could give us a disease or make us sick. Our feelings of disgust have helped keep us safe for hundreds of generations. People can usually sense trouble with a car from noises, vibrations, or smells. An experienced driver can even tell where the problem is. Instinctive computing aims to detect anomalous events from seemingly 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. Many electronic devices also provide pervasive ambient data streams, such as mobile phones, surveillance cameras, satellite images, personal data assistants, wireless networks and so on.

Intuition is a subconscious perception without thinking. Drawing portraits upside down allows novice artists to reproduce lower-level image features, e.g., contours, while reducing interference from higher-level face cognition [33]. A study shows that our subconscious intuition detects shape anomaly more accurately than conscious judgment [34]. Human-like perception systems have potential for remote sensing, virtual reality, medical discovery, autonomous space exploration and artificial organs that extend our perception. The peripheral vision of the redundant information enables us to detect anomalies from seemingly disconnected ambient data that we take for granted. Robertsson, et al [35] developed artificial sensor models for olfaction and manipulation, which enable knowledge discovery in a sensor web. Krepki and his colleagues [36] developed the Berlin Brain-Computer Interface (BBCI) as a potential HCI channel for knowledge discovery. Derived from an interface for physically challenged people, the brain-computer interface enables information retrieval directly through the human brain. In addition, it provides feedback regarding human attention, interests and emotion directly to an integrated computer. For decades, information analysts have been searching for ways to incorporate an expert's preference, style, attention, rhythm and other properties of intelligence into a knowledge discovery system. Unfortunately, most existing user-modeling methods are both invasive and indirect. A brain-computer interface shows us a potentially ambient approach to solving the problem.

Reproduction is a means for immortality. The instinct to have sex is one of the most potent we possess. It is vital if we are to produce the next generation. It has a great impact on the way we look, the way we smell and what we possess, which can attract the ideal mate [32]. Computational self-reproduction has been studied for half of a century. Von Neumann proposed a cellular automata to simulate the process [37]. However, so far, most of computational models are asexual. Today, online sexual interaction pushes technologies to the edge. Studies about sexual objects and interaction emerged, i.e., the computer vision model for detecting nude figures in a picture [38].

Learning upgrades instinctive programs. In 1896, James Mark Baldwin proposed that individual learning can explain evolutionary phenomena that appear to require inheritance of acquired characteristics [39]. The ability of individuals to learn can guide the evolutionary process. Baldwin further proposed that abilities that initially require learning are eventually replaced by the evolution of genetically determined systems that do not require learning. Thus learned behaviors may become instinctive behaviors in subsequent generations, without appealing to inheritance.

In the following sections, we will review the case studies for virtual forage, vigilance, intuition, reproduction and learning.

4. Virtual Forage

Today, ambient information is collected everywhere, from our shopping habits to web browsing behaviors, from the calls between businesses to the medical records of individuals. Data is acquired, stored and gradually linked together. In this massive data there are many relationships that are not due to chance, but transforming data into information is not a trivial task. Data is obtained from observation and measurement and has by itself little intrinsic value. But from it we can create information: theories and relationships that describe the relationships between observations. From information we can create knowledge about high-level descriptions of what and why, explaining and understanding the fundamental data observations.

4.1. Information Foraging

Many great discoveries in history were made by accident and sagacity. True serendipity emerges from random encounters, such as in daydreaming [40-42]. In Beale’s study [43], an intelligent system was designed to maximize pseudo-serendipity [44], which describes accidental discoveries of ways to achieve a desired goal. Beale introduces a synergistic interaction scheme that includes interactive data mining and a novel genetic algorithm to support serendipitous discoveries. Beale intends to answer questions such as: “what is interesting?” and “what is surprising?” In Beale’s study, the high dimensional data are mapped to a visual space where data are clustered by pseudo-physics properties such as mass-spring relations. This method allows the user to interact with the data space from different perspectives and hypotheses.

Analytical models intend to reveal inner structure, dynamics or relationship of things. However, they are not necessary intuitive to humans. Conventional scientific visualization methods are intuitive but limited by dimensions and resolutions. To bridge the gap, transformation algorithms are designed to map the data from an abstract space to an intuitive one. For example, a spectrogram maps an invisible sound to a visible frequency-intensity-time space. The convergence of scientific visualization and data mining creates a new domain for visual data mining. Seeing and understanding together enable humans to discover knowledge and deeper insight from a large amount of data [45]. This approach integrates the human’s Ambient Intelligence with analytical computation to form a coherent knowledge discovery environment.

4.2 Virtual Food-Chains

Kurt Letwin [102-103] said: "Our behavior is purposeful; we live in a psychological reality or life space that includes not only those parts of our physical and social environment to us but also imagined states that do not currently exist." We all work along a metaphor of ‘food chains’. Modern organizations hunger for resources and profit. In a factory, a manager is responsible to his boss and clients (providers). On the other hand, the manager is also a provider to his staffs and suppliers. The manager has to maximize his time to correspond with his boss and clients on a daily basis, while minimizing his time dealing with the problems from suppliers and staffs. Fig. 1 illustrates the mental map of the ‘food chains’ of a factory manager.

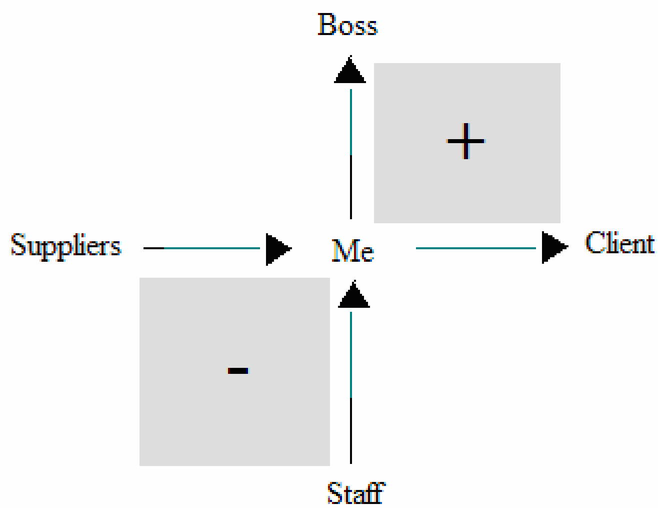


Fig. 1 Graphical user interface inspired by the food chains at workplace, where the user positions his boss on his North, client on East, staff on South and suppliers on West. The mental map helps him to organize daily business.

Unfortunately, modern electronic devices overwhelm us with information. For example, emails on the handheld PDA Blackberry™ are arranged in a linear order. Browsing through a long list of emails on a mobile phone at an airport can be miserable. Why don’t we design a graphical interface that projects an individual’s cognitive map? Given a sequence of messages, we can translate the message identifications into a two-dimensional quad-space, where supply-demand relations are defined as food chains, where the user positions his boss on his North, client on East, staff on South and suppliers on West. The mental map helps the user to organize daily business.

4.3 Near-Field Interactions

Wireless devices enable users to interact with local information services, such as Internet, vending machines, cash machines, and check-out desks, normally within 20 meters. 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 positioning system can estimate the distance between the access point and the wireless device [46]. 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.

Fig. 2 shows a screen capture of the wireless laptop positioning output. It shows the mobile users work near the wireless access points and power supplies. It is a novel tool to study the human dynamics from ambient data. Combined with multi-modal sensors, such as infrared and magnetic signals, the positioning accuracy can be further improved. The widely distributed open sensory system also raises serious concerns about data privacy [47]. Fig. 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 Web. The identity of users is replaced with a dot to preserve individual privacy.

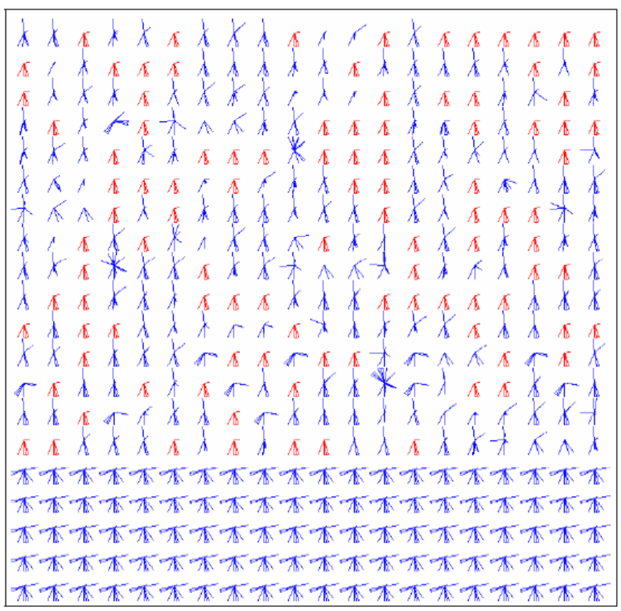
Fig. 2 Left: CMUSky wireless network device location system. The yellow dots show the dynamic patterns of mobile users. Right: Saharan ants made interesting forage patterns.

4. Vigilance of vulnerability

Network security is vital to our economy and personal rights. Detecting the vulnerability of a network in real-time involves a massive data space and intensive processing. Can we use instinctive computing to detect the vulnerability and anomaly?

We have developed a general visualization system for rendering at least 10,000 points and each point has at least 64 attributes in real time. An important part of the pre-processing task is to normalize the continuous data, so each attribute can have the same level of influence when comparing one data to another (calculating the Euclidean distance).

The normalization is performed dividing each attribute by the maximum attribute's value of the whole data scanned during a period of time. To visualize each network connection and their 41 attributes in 2D, we use the star glyphs, where the dimensions are represented as equal-spaced angles from the center of a circle and each axis represents the value of the dimension. Fig. 3 shows 400 network connections displayed on a Glyph form. The glyphs highlighted on red are connections that have similar attributes and consequently similar glyph's form. The glyphs on the bottom are connections from a DoS (Denial of Service) attack and, comparing to all the other connections, it is easy to remark that they present an abnormal form.



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Once the clusters are created, it is necessary to organize them, so they can be dispersed in a proper way, making an easy visualization. Several methods can be used: Principal Component Analysis, Kohonen Self Organizing Maps (SOMS) [48] and Multidimensional Scaling (MDS) [49-50]. Both SOMS and MDS were tested on the algorithm. The MDS presented a faster computational time. That is why it was chosen for the algorithm.

The goal of the MDS algorithm is to organize a multidimensional data on a two dimensional graphic by coordinate pairs (x,y). The Cartesian plane makes axes explicit and it is easier to organize data according to their characteristics. The idea of the MDS is to measure all the data distance in an n-dimensional space and place it on 2D display so they obey the same mutual distance relationship. However, a perfect 2D configuration is not always possible. Let d_{ij} be the multidimensional distance between a point i and j, calculated with the Euclidean distance. Let also δ_{ij} be the 2D distance between the same point i and j calculated with the Pythagorean Theorem, $\delta_{ij} = \sqrt{x^2 + y^2}$. If $d_{ij} \neq \delta_{ij}$, then there is a stress between the data and 2D representation. The stress is minimized with a Simplex optimization algorithm [51].

In the Simplex algorithm, first, we randomize an n-vector of independent variables as the initial point to calculate the stress. Then, it moves the point of the Simplex where the stress is largest through the opposite face of the Simplex to a lower point. Such reflections are constructed to conserve the volume of the simplex, then it will maintain its nondegeneracy. When it can do so, the method expands the Simplex in one or another direction to take larger steps. When it reaches a "valley floor," the method contracts itself in the transverse direction and tries to ooze down the valley. If there is a situation where the Simplex is trying to pass it, it contracts itself in all directions, pulling itself in around its lowest point. At this point, we get the minimum stress.

$$stress = \frac{\sum_{i<j} (d_{ij} - \delta_{ij})^2}{\sum_{i<j} d_{ij}^2}$$

Because of its complexity, the program splits the calculation into some phases. In every phase, it will calculate the minimum stress and organize them accordingly until it has reached the globally minimum stress. Thus, it is possible to watch the glyph's movements finding the best organization among them. Once the equation above is minimized, the data positions are set and organized, respecting its distance relationship with a minimum error.

The clusters organize the data dynamically, providing to them an approximate position next to the cluster associated to them. Fig. 4 displays an example of the implemented algorithm. The figure shows the MDS organization of the clusters in form of glyphs and a zoom of a cluster (in red), where it is possible to visualize the data associated to it.

The program supports a real-time application and the MDS organization algorithm runs in an on-the-job mode. Each cluster, here, is represented by a blue glyph. If users want to observe each data from the selected cluster, the application also provides an automatic "zoom in" every time the mouse is clicked on one of the clusters. Besides that, the tool also can be displayed in a multi-monitor mode, where different types of data can be placed in different monitors.

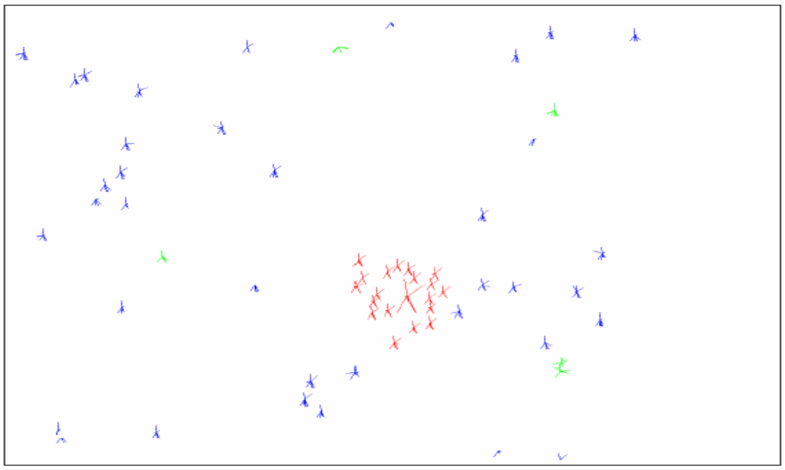

Fig. 4. Incrementally clustering. The glyphs in red are the data from a highlighted cluster. The glyphs in blue and green are the other clusters organized with the MDS algorithm.

Human vision has about 0.1 second vision latency [98] which has been an important factor in modern video and movie technologies. In principle, a system need not update data faster than human's response time. In light of this, we can use the human latency to design many novel human-centric computing algorithms that incorporate the latency factor. Many visualization methods involve time-consuming algorithms for clustering and optimization. Instead of waiting for minutes to see the updated results, the latency-aware algorithms are designed to synchronize with the speed of human vision by incremental updating. This should create a new philosophy of algorithm design.

We tested the models with the data from KDD CUP 1999 [52]. This data represents thousands of connections with 41 different attributes, including continuous and discrete attributes. The system successfully demonstrated its capability of rendering the anomalous events, such as the DoD attacks, in both stationary and dynamic visualization.

5. Human-like sensors

Human sensors are great inspirations for designing an efficient perception and communication system. They can also help us to diagnose diseases from ambient information.

5.1 Multi-resolution sensing

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. 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, constants a and b, the relation can be expressed as:

$$Y = -a \cdot log(X) + b$$

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 [53], eye gaze tracking and face detection technologies are applied to optimize the throughput of a wireless mobile video network. The objective of this task is to formulate a feedback control model, where the network traffic is a function of the visual attention. Given a number of camera live video channels with adjustable resolutions high and low that are arranged on a monitor screen, find the minimal network traffic as the computer detects which video channel is selected.

Fig. 5. The eye gaze tracking system for multiple video resolutions

To collect the lab data, the system needs to sense an operator’s attention ubiquitously by tracking user’s eye gaze on the monitor. Researchers at Ambient Intelligence Lab use an eye-tracking device with two infrared light sources. The camera can capture the eye gaze at 60 frames per second and the accuracy of 3 degrees. In the experiment, the operator uses their eyes to switch the video channels from a low resolution to a high resolution. The traffic monitor software records the real-time data flow.

From the empirical experiments it is found that multiple resolution screen switching can reduce the network traffic by 39%. With eye gazing interface, the throughput of the network reduced about 75%. Combining an eye tracking and face detection in the video, the overall throughput reduction reaches about 88%.

5.2 Tongue inspection

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 [54, 56]. 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 this ancient knowledge base. For example, the computer-based arterial blood-volume pulse analyzer is a ‘rediscovery’ of the diagnostic method originated from ancient TCM [55].

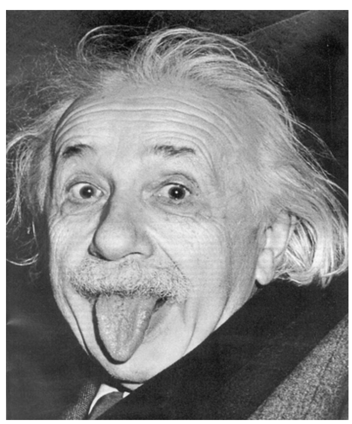

Fig. 6. According to the medical doctor, professor and author Claus Schnorrenberger from German Research Institute of Chinese Medicine, Einstein’s tongue[1] reveals that he has probably suffered from insomnia. He may have been affected by a stomach disorder and constipation [56].

[1] Albert Einstein stuck his tongue out at obtrusive press people and paparazzi on his 72nd birthday, March 14, 1951. He once stated, "A man's interactions with his fellow man are often not so different from a dog's interactions with a fellow dog"[100].

Visual inspection of the tongue has been a unique and important diagnostic method of Traditional Chinese Medicine (TCM) for thousands of years. The inspection of the tongue comprises the inspection of the tongue body and the coating. In the study [57], 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 a Probability Neural Network, the model reveals the correlation between the colon polyps and the features on the tongue.

The study shows the potential of inexpensive mobile cameras playing a role in healthcare. TCM diagnosis is not a replacement of the modern diagnostic technologies such as MRI, CT, Ultrasound, DNA, but an alternative tool for an 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.

6. Reproductive Aesthetics

The instinct to have sex is one of the most potent we possess. It's vital if we are to produce the next generation. It has a great impact on the way we look, the way we smell and what we possess, that can attract the ideal mate [101].

Computational self-reproduction has been studied for half of a century. John von Neumann [37] proposed cellular automata to simulate the process. However, so far, most of computational models are asexual and mechanical. Online sexual interaction pushes technology to its edge. Studies about sexual objects and interaction emerged. A computer vision model has been developed for detecting nude figures in a picture [38].

6.1 Sexuality

The English writer William Shenstone once said: "Health is beauty, and the most perfect health is the most perfect beauty." Why do people like symmetric faces and bodies? A simple explanation: symmetric shapes indicate fitness and good health.

In every century, three body parts - breasts, waists and thighs - are more often referred to as more beautiful than other body parts. Psychologists Devendra Singh and Adrian Singh show that men have only one thing on their minds: a woman's WHR - waist-hip ratio, calculated by dividing waist circumference by that of the hips. In the Royal Society journal, Proceedings of the Royal Society, Biological Sciences [58], they analyze thousands of examples from British literature from the 16th to 18th centuries with Peter Renn of Harvard University to show that what men find attractive today was also true hundreds of years ago: a narrow waist and thus an hourglass shape.

Modern science reveals that an hourglass shape in women is associated with relatively high levels of the hormone estrogen. Since estrogen levels influence fertility, men seeking to pass their genes to the next generation would do well to pick hourglass-shaped women. As a corollary, a sizeable belly is reliably linked to decreased estrogen, reduced fecundity and increased risk for major diseases according to research conducted over the past decade.

6.2 Detecting Human Body Features

From a computer vision point of view, detecting features from 3D body scan data is nontrivial because human bodies are flexible and diversified. Function fitting has been used for extracting special landmarks, such as ankle joints, from 3D body scan data [59-60], similar to the method for extracting special points on terrain [61]. Curvature calculation is also introduced from other fields such as the sequence dependent DNA curvature [38]. These curvature calculations use methods such as chain code [62], circle fit, ratio of end to end distance to contour length, ratio of moments of inertia, and cumulative and successive bending angles. Curvature values are calculated from the data by fitting a quadratic surface over a square window and calculating directional derivatives of this surface. Sensitivity to the data noise is a major problem in both function fitting and curvature calculation methods because typical 3D scan data contains loud noises. Template matching appears to be a promising method because it is invariant to the coordinate system [59-60]. However, how to define a template and where to match the template is challenging and unique to each particular feature. In summary, there are two major obstacles in this study: robustness and speed. Many machine learning algorithms are coordinate-dependent and limited by the training data space.

An Analogia (Greek: αναλογία, means ‘proportion’) Graph is an abstraction of a proportion-preserving mapping of a shape. Assume a connected non-rigid graph G, there is an edge with a length u. The rest of the edges in G can be normalized as $p_i = v_i / u$. Let X and Y be metric spaces d_X and d_Y. A map $f: X \rightarrow Y$ is called Analogia Graph if for any $x,y \in X$ one has $d_Y(f(x),f(y))/u = d_X(x,y)/u$.

Use of methods similar to Analogia Graph is common in the arts. The Russian Realism painter Ropin said that the secret of painting is “comparison, comparison and comparison.” To represent objects in a picture realistically, a painter has to constantly measure and adjust the relationship among objects. “You should use the compass in your eyes, but in your hands,” Ropin said. Instead of using absolute measurement of the distances and sizes, artists often use intrinsic landmarks inside the scene to estimate the relationships. For example, using numbers of heads to estimate the height of a person and using length of the eyes to measure the length of a nose, and so on. Fig. 7 is an Analogia Graph of a human body.

Using this artistic approach, we can create a graph where nodes represent regions and are connected to each other by edges, where the weight is defined as the distance between the nodes in proportion to the height of the head. Initially, we stretch the graph such that it overlays the entire body. We then create a link between each node and its respective counterpart. We link the head, shoulders, arms, elbows, hands, neck, breasts, waist, legs, knees, and feet to their respective regions. There is some tweaking required to assure that the waist region does indeed cover that area. Here we run a quick top-down search through the plane slices until there is at least two disjoint areas, which we consider to be the middle of the waist. This change also makes modifications to where the knees and breasts are, and how large their regions are.

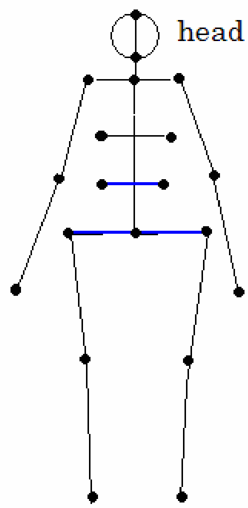

Fig. 7. Analogia graph of a human figure.

We take into account that not every subject has all four limbs. Our algorithm still accepts the scan if such items are missing, such as half an arm or half a leg. It is also amenable to a complete loss of an arm or leg by looking at the expected ratio versus the real ratios when determining the length of each particular region.

However convenient it is to find such broad range of regions, it is not possible to expand this algorithm to find more details like specific fingers, toes, ankle joints, or the nose. These searches are more complicated and require additional template fitting per feature and would significantly reduce the algorithm’s run time.

We found that the intrinsic proportion method can reduce the search space by an order of magnitude. In addition, it reduces the risk of finding the local optima while searching the whole body.

Intrinsic proportion measurements have been used in architecture and art for thousands of years. Roman architect Vitruvius said that the proportions of a building should correspond to those of a person, and laid down what he considered to be the relative measurements of an ideal human. Similarly in art, the proportions of the human body in a statue or painting have a direct effect on the creation of the human figure. Artists use analogous measurements that are invariant to coordinate systems. For example, using the head to measure the height and width of a human body, and using an eye to measure the height and width of a face.

Fig. 8 shows the distribution of head to body proportions calculated from the CAESAR database. The results show that on average a human is six to eight heads tall. Based on our observations from one hundred 3D scan data sets of adults from sixteen to sixty-five years old, including subjects from North America, Europe and Asia, we found that the length of one and a half head units from the bottom of the head is enough to cover the chest area. In addition, the chest width is about three heads wide. The chart on the right of Fig. 8 shows an output from the intrinsic proportion calculation based on the sample from CAESAR database.

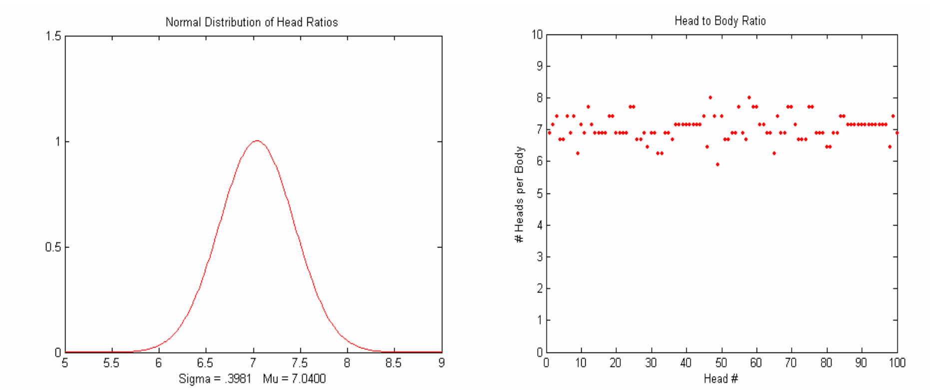

Fig. 8. Normal distribution of heads per body (left) and spread of actual number of heads per body size for all models (right).

6.3 Privacy algorithm

What is privacy? Privacy is vulnerability. People are concerned about their own or spouses' bodies for sexual reasons. Men or women would feel insecure to exposing their private parts because of the fear of imperfectness. In addition, men feel insecure as spouses or girlfriends expose their body to other men. Overall, religion and culture play a great role here.

The rapidly growing market for 3D holographic imaging systems has sparked both interest in security applications and privacy concerns for travelers. Current body scanners use a millimeter-wave transceiver to reflect the signal of the human body-and any objects it carries, including weapons hidden under clothing. However, these high-resolution scanned images also reveal human body details[2]. This has caused airport and transportation officials in several countries to refuse to test the scanners until researchers find more suitable ways to conceal certain parts of the human body.

At Carnegie Mellon University's Ambient Intelligence Lab, we are working to develop a method that can efficiently find and conceal humans' private parts [63]. Developing a

[2] www.pnl.gov/energyscience/01-02/art1.htm

system that's both robust and fast, however, presents a challenge. Many machine-learning algorithms are coordinate-dependent and the training data space limits them. Some algorithms only work within small bounding boxes, which is unacceptable since the system must detect the boxes before the algorithm is executed, and the boxes often aren't amenable to noise. For example, a feature-detection algorithm takes one hour to process, too long to be useful for a security screening system.

Fig. 9. The three-dimensional holographic imaging systems can detect contraband beneath clothing, yet they raise privacy concerns due to the detailed human figure that is revealed.

The privacy-aware computer algorithm we developed uses the scanner to create a 3D point cloud around the human body. Since the millimeter-wave signal can't penetrate the skin, the scanner generates a 3D human surface. Furthermore, since subjects undergoing a security search are typically standing with their arms to the side, we can segment the 3D dataset into 2D contours, which significantly reduces the amount of data processing.

Unfortunately, examining each slice from top to bottom is computationally expensive. To solve that problem, we used analogous measurements invariant to coordinate systems to reduce the search space with intrinsic proportions, for example, using the height of a person's head to locate the chest.

Furthermore, to determine whether the shape of a 2D contour contains defined features, we use coordinate-invariant shape properties such as height ratios and area ratios that are independent from particular poses or a specific coordinate system.

Template matching is an image-registration process that matches a surface containing known relevant information to a template of another surface. A similarity function matches the two surfaces.

Two issues arise in applying template matching on the regions of interest. First, you need to create a suitable template. Second, you must select a similarity function so that a minimization algorithm can align the template onto the region of interest. For each plane of the scan data, you can remove the back part of the body contour. By assigning the horizontal axis between the two points with the greatest distance, the model can obtain the front part of the body contour. We used radial basis functions (RBF) to configure the template for a female breast pattern, for example, and the nonlinear regression mode to match the template with the scan data.

We tested the algorithm with a database subset from the Civilian American and European Surface Anthropometry Resource project[3]. The subset contained data for 50 males and 50 females age 16 to 65. Fifty of the subjects were North American, 24 were Asian, and 26 were from Italy and the Netherlands.

We designed the experiment to test whether the algorithm can find the breast features from known female and male scan data samples. Figure 2 shows these test results.

From the plot, we can see that two distinguishable groups coincide with each subject's gender. The male subjects tend to have no curvature features and lie in the lower-left range of the graph, whereas female subjects demonstrate curvature features and lie in the upper-right range of the graph. There's a "dilemma" zone where some overweight males do have curvature features. However, the overlapped zone is small, less than 8 percent of the total 100 samples.

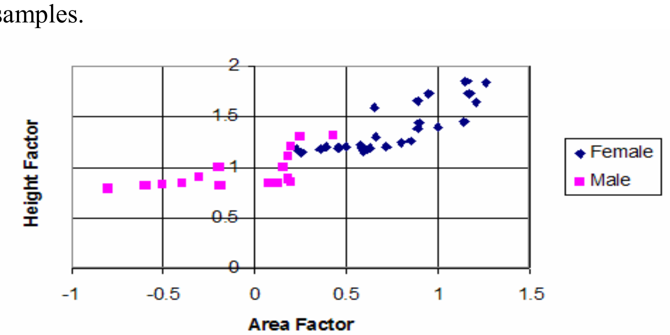

Fig. 10. Classification results. Template matching separated males without curvature features from females with curvature features.

After we calculate the area and height factors, we determine the private feature areas. Once the system finds those areas, it reduces the polygon resolution so that the area is either blurred or transparent. Fig. 10 and 12 show the results of blurring and transparency, respectively.

To determine the usefulness of these techniques in meeting privacy concerns, we conducted empirical usability tests based on two sets of the surface-rendering methods:

[3] CAESAR database: www.sae.org/technicalcommittees/caesar.htm

blurring or transparency at six levels, shown as Fig. 10 and 11. The study included 10 males and 10 females, age 19 to 57.

6.3 Priority of instincts

We have conducted two experiments that reveal how people prioritize instincts between security and privacy [63]. As we know, security has higher priority over privacy under a certain circumstances.

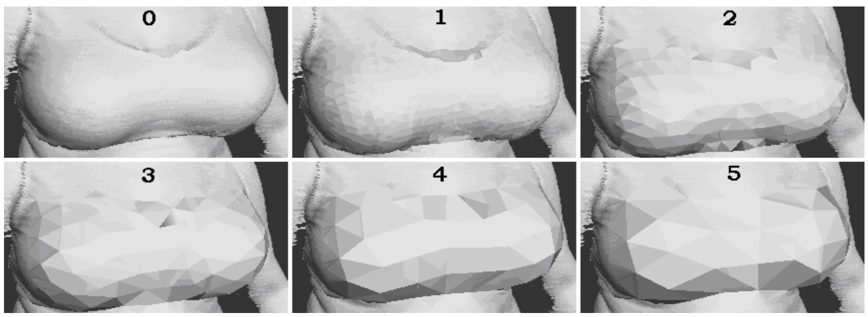

Fig. 10 The blurring scale

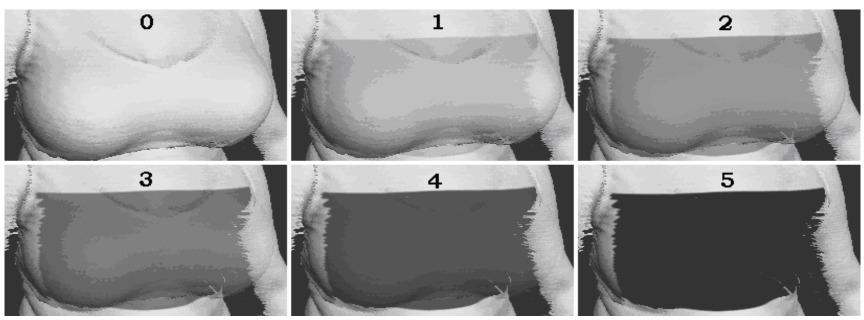

Fig. 11 The transparent scale

In the first study, we told the male subjects to imagine they (or their girlfriends or wives) had to walk through a 3D holographic scanner that would display resulting images to airport security officials on duty. They were asked to choose between a blurred or transparent image. The men averaged a 4.8 on the blurred scale and a 4.2 on the transparent scale. When asked about their concern regarding walking through the scanner, the women averaged a 4.0 on the blurred scale and a 3.8 on the transparent scale.

In the second study, we told subjects to rate their concern about privacy versus security in a scenario where we would also observe others possibly trying to conceal weapons. Such oddities as a pocketknife between the breasts would be more difficult to detect in a very blurred mesh. The men averaged a 3.2 on the blurred scale and a 2.9 on the transparent scale. The women, on the other hand, averaged a 2.5 on the blurred scale and a 2.3 on the transparent scale.

The two usability studies indicate that different contexts can affect a subject's response and personal choice. In the first study, the men were more concerned about having their girlfriends or wives seen than the women were with how much they were seen. In the second study, almost every subject was willing to give up more privacy for the benefits of security and travel safety.

The development of the privacy algorithm is preliminary, and considers only one privacy-concerned area. However, it offers a feasible way to develop more robust privacy algorithms with available anthromorphics and physics databases. The method has been tested on 100 datasets from the CAESAR database. In both the blurring and transparency surface-rendering methods we studied, test subjects preferred to have the most privacy possible. However, the subjects adjusted their privacy concerns to a certain degree as they were informed of the security context.

7. Learning by virtual experiencing

According to Baldwin Effect [39], we are able to update our instincts from persistent learning. The result is automation. Many commonsense operations can be executed subconsciously. This principle can be applied to both human and machine. Fortunately, virtual reality technologies enable us to experience a simulated world without fatal risks, such as illness, falling and death.

7.1 BioSim game [64]

According to Constructism, we do not simply learn things but construct them. Understanding and solving biomedical problems requires insight into the complex interactions between the components of biomedical systems by domain and non-domain experts. This is challenging because of the enormous amount of data and knowledge in this domain. Therefore, non-traditional educational tools have been developed such as a biological storytelling system, animations of biomedical processes and concepts, and interactive virtual laboratories.

We developed a computer game to allow children to explore biomedical knowledge [64]. We designed a biological world model, in which users can explore biological interactions by role-playing "characters" such as cells and molecules or as an observer in a "shielded vessel", both with the option of networked collaboration between simultaneous users. The system architecture of these "characters" contains four main components: 1) bio-behavior is modeled using cellular automata, 2) bio-morphing uses vision-based shape tracking techniques to learn from recordings of real biological dynamics, 3) bio-sensing is based on molecular principles of recognition to identify objects, environmental conditions and progression in a process, 4) bio-dynamics implements mathematical models of cell growth and fluid-dynamic properties of biological solutions.

The principles are implemented in a simple world model of the human vascular system and a biomedical problem that involves an infection by Neisseria meningitides where the biological characters are both white and red blood cells and Neisseria cells. Our case studies show that the problem-solving environment can inspire user’s strategic and creative thinking. Fig. 12 and 13 shows an example of the learning process.

7.2 Virtual reality training for robots

The feasibility of using virtual reality to train nonhumans is demonstrated in studies that used virtual reality with rats. Hölscher et al [65] found that rats are capable of navigating in virtual environments. In parallel, Nekovarova & Klement [66] found that rats can learn to press levers for rewards when certain configurations appear on a computer screen. Therefore, while previously only humans and primates were thought to be able to navigate virtual worlds, these rat studies show that non-primates can be trained to navigate them as well.

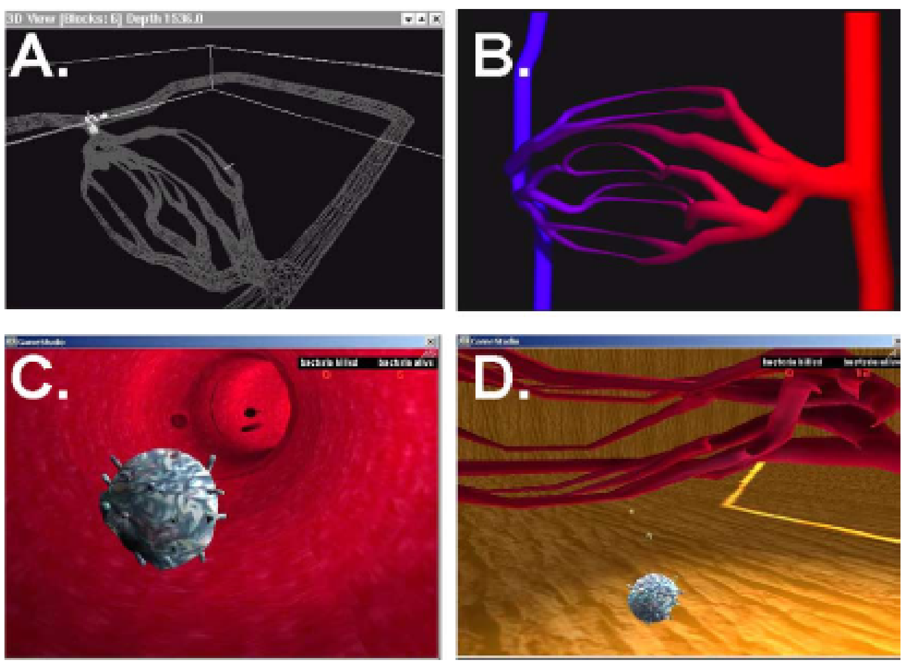

Fig. 12. World model and biological characters implemented in the game. (A) Wireframe model of the vascular system world model; (B) 3D photorealistic model showing arteries and capillaries; (C) the macrophage (white blood cell) is inside the blood stream with red blood cells; (D) after actively moving out of the blood stream, the macrophage approaches bacteria that infected human body tissue.

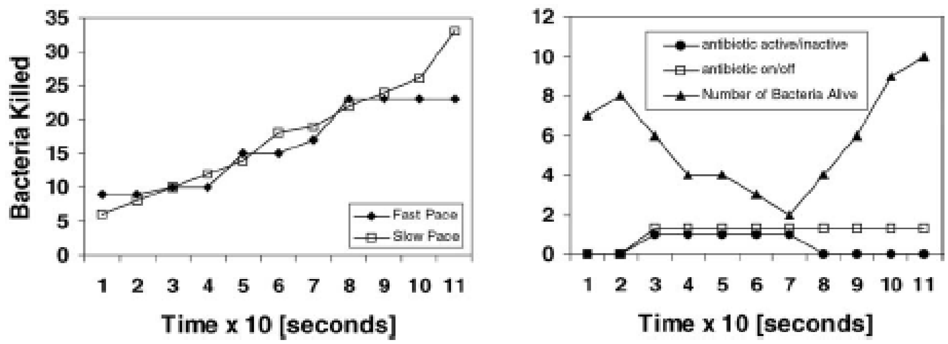

Fig. 13. Strategies against bacterial infection that can be explored in the game, speed of macrophage movement (left) and use of antibiotics (right). The fast pace strategy often leads to missing targets. The slow pace strategy gains steady capture rate. The use of antibiotics can be limited by gradual development of bacterial resistance. At that point, administration of drug does not inhibit bacterial growth.

If rats can navigate in virtual reality and humans can train in virtual reality, can robots be trained in virtual reality? If so, because humans who are trained in virtual reality can perform equal to or better than humans who are trained in real life, the possibility exists that training a robot in virtual reality may result in improved (faster and more accurate) performance than training a robot in real life.

Fig. 14. "How many robots to go before they can learn the meaning of death?" The death instinct is a paradox of instinctive computing. It is possible to learn it through analogy [94-95] or virtual reality. Copyright© Yang Cai, 2007

For example, Virtual Reality Medical Center[4] developed a simulator DARWARS [67] that enables soldiers to navigate a virtual shoot house before running through a real-life shoot house that had a different layout; and their improved speed in the shoot house demonstrates that spatial skills learned in virtual reality transferred to real life. There is thus reason to believe that if a robot were trained in navigational skills in virtual reality, it would learn improved spatial skills that transfer to previously unexplored environments.

On the other hand, *virtual reality enables robots to learn instinctive computing* that are impossible or too expensive to learn in real-life, such as to learn the meaning of 'death.'

8. Ambient Intelligence

As the volume and complexity of information grows exponentially, information-overload becomes a common problem in our life. We find an increasing demand for intelligent systems to navigate databases, spot anomalies, and extract patterns from seemingly disconnected numbers, words, images and voices. Ambient Intelligence (AmI) is an emerging paradigm for knowledge discovery, which originally emerged as a design language for invisible computing [68] and smart environment [13,69,70,71]. Since its introduction in the late 1990's, this vision has matured, having become quite influential in the development of new concepts for information processing as well as multi-disciplinary fields including computer science, interaction design, mobile computing and cognitive science.

As a part of Artificial Intelligence, Ambient Intelligence is a subconscious approach for ubiquitous computing, which inspires new theories and architectures for *'deep interactions'* that link to our instinct, such as empathic computing [72].

In a broad sense, Ambient Intelligence is perceptual interaction, involving common sense, serendipity, analogy, insight, sensory fusion, anticipation, aesthetics and emotion, all modalities that we take for granted.

True Ambient Intelligence requires instinct computing! We discover knowledge through the windows of our senses: sight, sound, smell, taste and touch, which not only describe the nature of our physical reality but also connect us to it. Our knowledge is shaped by the fusion of multidimensional information sources: shape, color, time, distance, direction, balance, speed, force, similarity, likelihood, intent and truth. Ambient Intelligence is not only perception but also interaction. We do not simply acquire knowledge but rather construct it with hypotheses and feedback. Many difficult discovery problems become solvable through interaction with perceptual interfaces that enhance human strengths and compensate for human weaknesses to extend discovery capabilities. For example, people are much better than machines at detecting patterns in a visual scene, while machines are better at detecting errors in streams of numbers.

[4] Dr. Mark Wiederhold, president of VRMC: www.vrphobia.com is a principal investigator of the project.

9. Empathic Computing

Empathic Computing aims to enable a computer to understand human states and feelings and to share the information across networks. Instinctive computing is a necessary foundation of empathic computing.

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 [73]. Alan Turing argues that machine intelligence can be tested by dialogs through a computer keyboard [74-76]. 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'.

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 to 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 [78] 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 the Internet to communicate the signal remotely.

Empathic sensor webs provide new opportunities to detect anomalous events and gather vital information in daily life. Their 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 [99] 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. To avoid the potential information avalanches in the empathic sensor, there are instinctive computing solutions for information reduction on the source side, for instance, applying the power law for multi-resolution channel design and interacting mobile sensors with stationary sensors.

There are a few prototypes of empathic computing. For example, Fig. 15 shows the wearable empathic computing system that is to detect an instance of an individual falling down. 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.

Fig. 15. Wearable sensor that detects anomalous events

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 [79]. 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 [80] 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 [81-82], HomeNet [83], and Philips' HomeLab [84]. Furthermore, Bodymedia has developed the armband wearable sensor [85-86] that tracks body temperature, galvanic skin response, heat flux, and other data. However, most of products have not reached the scale of economy.

10. Conclusions

Early Artificial Intelligence scholars used a 'top-down' approach to study human behavior. They focused on logic reasoning and languages. The more they went deep into the human's mind, the more they felt the need to incorporate human instincts including perceptual intelligence, empathy, and commonsense. For example, Herb Simon combined logic model with pictorial representation in CaMeRa model [87]. John Anderson extended ACT-R [27] with sensory function. However, the 'top-down' approaches have their limitations. Herb Simon saw the gap between the sequential logic reasoning and parallel sensing. He challenged his students: “have you found any neural network that is capable of solving the Hanoi Tower Problem?” Perhaps instinctual computing is a potential bridge between the two.

The fundamental difference between existing machines and a living creature is *Instinct!* Instinctive computing is a computational simulation of biological and cognitive instincts. It is a meta-program of life, just like universal gravity in nature. It profoundly influences how we look, feel, think, and act. If we want a computer to be genuinely intelligent and to interact naturally with us, we must give computers the ability to recognize, understand, even *to have* and express primitive instincts.

In this paper, we reviewed the recent work in this area, the instinctive operating system, and potential applications. The paper proposes a ‘bottom-up’ approach that is to focus on human basic instincts: forage, vigilance, reproduction, intuition and learning. They are the machine code in human operating systems, where high-level programs, such as social functions can override the low-level instincts. However, instinctive computing has been always a default operation. Instinctive computing is the foundation for Ambient Intelligence as well as Empathic Computing.

In his book "Philosophical Investigations", Ludwig Wittgenstein states: "The aspects of things that are most important for us are hidden because of their simplicity and familiarity. One is unable to notice something - because it is always before one's eyes. The real foundations of his enquiry do not strike a man at all. Unless that fact has at some time struck him. And this means: we fail to be struck by what, once seen, is most striking and most powerful." Perhaps, Instinctive Computing is a key to unveiling the hidden power in human dynamics.

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