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NEW DIRECTIONS FOR MEDICAL ARTIFICIAL INTELLIGENCE

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Abstract—The past decade has seen significant advances in medical artificial intelligence (MAI), but its role in medicine and medical education remains limited. The goal for the next decade must be directed towards maximizing the utility of MAI in the clinic and classroom. Fundamental to achieving this is increasing the involvement of clinicians in MAI development. MAI developers must move from "pet projects" toward generalizable tasks meeting recognized clinical needs. Clinical researchers must be made aware of knowledge engineering, so clinical data bases can be prospectively designed to contribute directly into MAI "knowledge bases". Closer involvement of MAI scientists with clinicians is also essential to further understanding of cognitive processes in medical decision-making. Technological advances in user interfaces—including voice recognition, natural language processing, enhanced graphics and videodiscs—must be rapidly introduced into MAI to increase physician acceptance. Development of expert systems in non-clinical areas must expand, particularly resource management, e.g. operating room or hospital admission scheduling. The establishment of MAI laboratories at major medical centers around the country, involving both clinicians and computer scientists, represents an ideal mechanism for bringing MAI into the mainstream of medical computing.

ARTIFICIAL INTELLIGENCE IN MEDICINE

The application of artificial intelligence (AI) techniques to medical problems has been a goal of computing since the development of high-speed digital computers. In the 1970s, medical artificial intelligence (MAI) was responsible for the highly successful MYCIN program, the very first expert system [1]. In the 1980s, the rapid proliferation of AI technology, combined with the greater availability of computers in the medical environment, led to an increasing number of medical expert systems, such as PUFF, CADUCEUS and INTERNIST [2]. As in the business world, expert systems in medicine validated themselves when compared against human "experts" [3]. For the first time, AI began to play a role in medical education as well [4]. At present, AI programs, such as expert system shells, are available for use on personal computers, and MAI is poised to become a significant factor in the medical computing environment as we head into the 1990s. Conspicuously absent on the MAI scene, however, is a firm sense of priority and direction for the development of new applications, and a sound program for their implementation into the mainstream of medicine. It is the goal of this paper to suggest, from a clinician's viewpoint, directions and priorities for the next decade of MAI applications, and suggest a mechanism to implement them.

Analogous to the introduction of a new drug, MAI must pass through a series of phases prior to widespread acceptance. In drug evaluations, Phase I is directed towards the preliminary evaluation of the new drug, establishing its toxicity (cost) and optimal mode of delivery. Phase I evaluations are often carried out on patients for whom all conventional therapy has failed, and expectations for dramatic response to the new treatment are low. Phase I testing does not establish exactly which patients would be most likely to benefit from the new agent. Phase II testing, by contrast, is designed to identify specific areas where the new treatment will be effective, and to verify in a larger number of cases the treatment's safety. Patients who are enrolled in these trials often have less advanced disease than those in Phase I studies, and it is expected that if a significant benefit exists, it will be identified in this phase. The groups of patients in Phase II trials are carefully selected, so that if only a small but distinct population benefits from the new treatment, they will not be lost in the "noise" of the heterogeneous population of non-responders. Once Phase II has identified specific groups most likely to respond to the new therapy, and has addressed any hitherto unexpected problems, Phase III evaluation begins. This phase employs the most effective schedule of administration in the patients most likely to benefit, in a head-to-head comparison against the current standard treatment for the same patients. In this way, the relative value of the new treatment compared to standard therapy is assessed. If the new method proves itself, it is accepted and approved for general use in the established "indications".

In this analogy, MAI has certainly progressed through Phase I testing. We know that the technology exists to deliver MAI without excessive cost. On the other hand, "dramatic responses" have been remarkably few. Even MYCIN and other medical expert systems have been more noteworthy as research projects than as medical advances. There is, at present, no consensus as to which applications are best suited to eventual application of MAI, nor is there any data to prove that MAI in any context provides clear-cut benefit over more conventional alternatives. We have not yet begun Phase II testing in earnest.

Following through with a systematic plan of evaluation for MAI applications, like that described for a new drug, would have several major advantages. It would force researchers to carefully screen and select the applications tested, to maximize the likelihood of success. At the same time, it would allow collection of data in carefully defined, homogeneous settings—so that other researchers, both clinicians and computer scientists, could assess the generalizability of the MAI system being tested to their own problem areas. "Single-use only" solutions, which work for the application developer but no one else, would be discouraged, in favor of more global applications. Once there was some level of agreement on the optimal targets for a given MAI system, then direct comparisons to the existing standard, whether it be human or "unintelligent" computer, can be carried out. The results of such a comparison would establish for the medical community the indications and effectiveness of the new MAI solution.

In order to identify application areas likely to respond to MAI techniques, it is imperative that practicing clinicians are involved in the planning stages of any new effort. Unfortunately, the clinician—the doctor who must ultimately use the technology—is so often left out of the loop in the critical early phases of development. A broad base of clinical expertise, particularly including non-computer-literate physicians, is essential to avoid generating a solution that is technically correct but technologically inaccessible for the average doctor. Development of interdisciplinary computing laboratories (combining physicians and computing specialists) should be explored to bring the expertise of the clinic and computer together.

On the other hand, clinical researchers must be made aware of the concepts and capabilities of knowledge engineering, and "knowledge engineers" should become involved in the design of clinical data bases. In this fashion, the data collected in clinical data bases, especially in research and academic settings, can be directly incorporated into "knowledge bases". These knowledge bases can feed forward into the development of expert systems and other MAI applications, and at the same time feed back to the clinician valuable information regarding the patients he or she is treating. Improved access to, and more efficient extraction of useful knowledge from, clinical data bases represents a major area where closer cooperation between physicians and MAI-oriented computer scientists can lead to significant gains in the 1990s. At the same time, a closer interaction between clinicans and computer scientists is needed if the oft-stated goal of improving understanding of the cognitive processes involved in clinical decision-making is to be achieved. Here again, careful selection of the appropriate "model system" is essential if computer-simulated decision making systems are to provide useful insight into the mind of the medical expert. Any computerized system of medical diagnosis or decision-making needs to be carefully evaluated, first for effectiveness in a carefully defined, homogeneous population ("Phase II"), and then in head-to-head comparison with the gold standard—the physician himself. Most importantly, computerized decision-aiding systems need to prove themselves not merely as good as a physician, but *better*, if they are truly to be accepted by the medical community (as opposed to the AI world). If clear-cut benefits really exist from using computers as medical decision-making aids, future MAI trials will have to be designed from their inception in ways that will allow these benefits to be demonstrated.

Physician acceptance of MAI in the 1980s has been hampered by relatively crude and cumbersome user interfaces, one of physicians' major concerns in evaluating new computer technology, [5, 6]. The 1990s hold the promise of major improvements of interface technology. In particular, natural language processing, voice recognition and improved graphics should be incorporated into future MAI efforts, as these all address major deficiencies in current user interfaces. Most important of all may be the development of videodisc technology and CD-ROM (compact disc-read only memory); in the image-oriented world of medicine, the ability to store and quickly retrieve large numbers of photographs, X-rays, etc. will become increasingly vital to any medical computing venture.

While MAI projects with direct clinical application, such as diagnostic tools for appendicitis, seem to capture the most glamor in AI circles, they are not always clinically useful. We already have physicians who are making the diagnosis of appendicitis on a daily basis, and they are aware of the limitations of their diagnostic acumen and have learned to practice within those limitations. Merely computerizing the diagnostic process does not extend the limitations, hence, it does not directly further patient care. Other MAI applications, however, may directly benefit physicians and patients in different ways. In particular, medical resource management is a fertile, yet underexplored, application area. An increasing level of cost-consciousness, brought about in part by diagnosis-related group payments (DRGs) and greater third-party payor surveillance, can be expected to pervade medicine throughout the 1990s. Clinicians and computer scientists together will need to identify applications, such as bed control (admission, discharge and transfer tracking), operating room and clinic scheduling, and supply ordering, where expert systems and other MAI techniques can increase cost-effectiveness unobtrusively. Such applications clearly need to be a priority area for the next decade.

Lastly, questions of hardware and software must be thoughtfully addressed in designing MAI systems for the immediate future. The extreme variety of personal and mini-computer systems in the present medical computing environment will surely continue over the short term. This diversity represents both a challenge and an opportunity for MAI designers. Compatibility issues should be addressed "up-front", preferably at the design stage, so that when a system proves its value it can be more easily transferred across hardware barriers. Once again, "single-use only" (or single *user* only!) projects must be abandoned in favor of more generalizable solutions as a prerequisite for widespread adoption of MAI.

AI IN MEDICAL EDUCATION

Intelligent computer-assisted instruction (ICAI) has developed in parallel with the entire field of MAI [4]. Given the mandate behind an increased role for medical informatics in medical education [7], its future growth seems assured. Nonetheless, many of the caveats stated above for MAI in general apply equally well to ICAI. In fact, problems of user interface and compatibility loom even larger in education than in actual practice. With ICAI, MAI is being introduced to a population who may be only marginally computer literate and who, because of monetary constraints, may have access to only a single type of computer hardware. Education-related applications need to rely more heavily on explanatory and error-diagnostic modules than standard MAI ones, so the need for close interaction between medical educator and computer scientist is great.

Perhaps the top priority for computer-aided medical education in the next decade is the careful selection of appropriate target areas. Medical educators, rather than computer scientists, will need to take the lead in this selection process, aided by careful studies aimed at identifying deficiencies in the current (non-computerized) medical education process. Even without waiting for the completion of such studies, several main targets for ICAI can be identified. Clearly, ICAI—especially when coupled with advanced technologies for graphic representation of information—provides a golden opportunity to provide "hands on" experience to students at all levels of training. As such, ICAI could potentially revolutionize medical training in the 1990s, by permitting exposure to patient simulators before physicians are called upon to treat the actual patient. In clinical practice, scenarios such as trauma management, critical care and cardiac arrest are usually handled by senior level physicians-in-training (residents), leaving junior residents, interns and students on the sidelines watching. Suddenly (generally on 1 July of the year), junior residents become senior residents and are now faced with the responsibility for these emergency situations. ICAI must be evaluated for its ability to ease this transition by more adequately preparing physicians-in-training without jeopardizing overall patient care.

Another potential role for ICAI is to compensate for the inevitable variations in experience that graduates of different medical schools and residency programs have. For example, a resident who trained in Southern California may never have seen a patient with frostbite, while another resident from the Northeast probably has never seen a rattlesnake bite. Yet when the two residents graduate and begin private practice in Colorado, they may encounter either of these conditions. Within the same city, residents in training at two different hospitals—one a tertiary referral center largely filled with patients with unusual conditions, the other an inner-city hospital populated with patients with neglected illnesses and trauma—will have vastly different experiences. Medical educators and residency program directors must begin to identify such regional and inter-hospital variations, and work with computer scientists to develop innovative instructional techniques which bridge these gaps.

Medicine is undergoing an evolutionary change with greatly increased attention being paid to "cost-effective" delivery of care. Yet most students and residents in "teaching" hospitals have little or no idea of the cost of the tests and services they are ordering. Professorial teaching rounds often stress the value of diagnostic tests far more than the costs, leading to a paradoxical situation where students learn a "shotgun" approach—order every test and you will never be caught without the right one. Such an approach is no longer tenable, given the fiscal realities of the immediate future. ICAI efforts to date have not seized the opportunity to incorporate monitors of cost-effectiveness into the overall outcome. Students participating in a computerized patient evaluation should receive feedback as to the total cost of the diagnostic tests they ordered, not just the end-result in terms of establishing the correct diagnosis. The computer should identify ways in which the student could have achieved the same end-result in a more cost-effective way, selecting only those tests critically necessary to make the proper diagnosis. Such an approach will, in part, require a rethinking of diagnostic strategies by medical educators as well. This would represent a valuable, perhaps even vital, "spin-off" of the use of computer technology in medical education.

Finally, medical educators must realize that patients themselves need medical education, and hence are legitimate targets for MAI efforts. The looming crisis of AIDS provides just one recent example of the need for large-scale public education measures as an integral part of the management of a disease. Computerized instruction is an ideal way to convey information directed to the specific needs of the patient, particularly when the subject is one so emotionally charged as sexual behavior and the risk of AIDS transmission. More conventional subjects of patient education, such as the need for monthly self breast examination and yearly mammography for women to reduce their risk of breast cancer, are also worthwhile targets for computerized instructional efforts. Direct measurement of the effectiveness of computer-aided instruction compared to conventional education, in terms of modifying patient behavior away from high-risk practices and toward preventative efforts, should be an integral part of the evaluation of any ICAI effort of this type. As an additional benefit, patient ICAI could potentially represent a "two-way street", with the computer asking for and recording information about the patient's current health practices and risk factors at the same time as it dispenses information about modifying them.

NEURAL NETWORKS IN MEDICAL APPLICATIONS

Neural networks (also called parallel distributed processors, neurocomputing, connectionist models and artificial neural systems) are one of the fastest growing and most innovative areas of computing. Neural networks represent an attempt to simulate biological information processing through massively parallel, highly-interconnected processing systems.

Neural networks offer the potential for solving complex, non-deterministic problems at very high speeds, the ability to recognize complex patterns, and the capability of rapidly storing and retrieving very large amounts of information. Neurocomputing has received considerable attention from the U.S. Department of Defense in a number of application areas, including data fusion (the rapid analysis of data from several different and diverse sources; normally from a variety of electromagnetic sensors), decision assistance, signal processing and intelligence gathering. Neural networks also have a number of important commercial applications, such as the dynamic solution of routing problems, image and handwriting recognition, systems modeling, speech generation, robot control and "expertless" expert systems [8, 9]. Several of these applications are also of interest in medicine.

Neural networks have a number of other potentially important medical applications, such as modeling the brain and nervous system functions, speech analysis and synthesis, X-ray and bacterial culture screening (for recognition of special types of disease patterns), patient monitoring, as control units for prosthetic devices, automatic diagnostic systems and the dynamic solution of complex allocation and routing problems in drug dosage administration, hospital resource allocation, and health care service.

Despite the current attention from the media, neural networks are not a new idea. In fact, neural network concepts, like so many important advances in AI, have their roots in medicine. Neural network research dates back to 1943, when Warren McCulloch, a physician, and Walter Pitts, a mathematical physicist, suggested that the complex computations occurring in the brain could be performed by a network of simple binary neurons performing elementary logical functions. The McCulloch–Pitts (M–P) neuron model had two types of inputs, an excitory input and an inhibitory input. The neuron summed the inputs and if the excitory inputs were greater than the inhibitory inputs, the neuron "fired", that is, generated an output. While the model, as stated, could account for logical processing, it did not show how information was stored or how intelligent behaviors were learned [10]. In 1949, Hebb postulated that knowledge was stored in the "connections between the neurons", and that "learning consisted of modifying these connections and altering the excitory and inhibitory effects of the various inputs". A number of early experiments with M–P-like neuron networks and Hebbian learning rules showed very interesting and impressive results [11].

Frank Rosenblatt made a major contribution to neural network research during this period with the development of the perceptron. The perceptron, an abstract system based on optical nerve structures, provided a simple model which permitted extensive mathematical analysis of neural networks. Rosenblatt also pioneered the simulation of these networks on a digital computer. However, Rosenblatt made claims for his perceptrons which aroused the ire of a number of other researchers in the field of AI. Marvin Minsky and Seymour Pappert of MIT conducted an in-depth mathematical analysis of the perceptron and Rosenblatt's claims, which culminated in the publication of their book *Perceptrons.* Minsky and Pappert proved theoretically that the perceptron model was very limited and could not handle large classes of realistic problems [12]. The release of Minsky and Pappert's work, followed by the untimely death of Rosenblatt in a boating accident, had a very dampening effect on neural network research. However, limited neural network study continued, even without much support and funding. The current wave of interest in neural networks began in 1982. John Hopfield, a prominent biophysicist, showed that artificial neural networks were capable of solving constrained optimizating problems (such as the "Traveling Salesman Problem", where a salesman must visit a number of cities in a minimum amount of time and without re-visits). He introduced the concept of a global energy function to characterize that state of the system, and showed that solutions to equations occupy the lowest possible energy states, and that artificial neural networks would stabilize or "anneal" to these low-energy states [13]. Since then, a number of new network and modified learning rules have been developed, some of which have demonstrated surprising capabilities. There are now sophisticated digital computer programs to simulate neural networks on personal computers, add-on neural network co-processing boards for personal and mini-computers, high speed connectivity machines that emulate neural networks, and new chips that simulate artificial neural systems.

Despite all the activity and the increased level of research support for defense applications, there still is a tremendous amount of work to be done. This is particularly true in the area of the theoretical understanding of the underlying structure of both biological and artificial neural systems, as well as the practical area of design and development of medical applications. However, MAI research and development will play a key role as artificial neural systems begin to realize their potential in the next decade.

INTELLIGENT GRAPHICS SYSTEMS

The development of the GUI (graphical user interface; familiar to most of us at the "desktop" metaphor of the Macintosh computer) during the past decade has marked a significant change in the way humans work with computer systems. The pioneering research of Xerox with Smalltalk was translated into a commerical success by Apple with its Macintosh computer. Steven Jobs'

NEXT computer system features an extrapolation and enhancement of the GUI. IBM's OS/2 Presentation Manager and its SAA (system application architecture) graphics standards for applications across the IBM product line, also indicate the computer industry's commitment to GUI-based interfaces. Intelligent graphics systems (IGS) represent the next logical development in this area. IGS can be defined as the integration of intelligence with the standard GUI (windows, icons, mouse, pull-down menus and dialog boxes) devices. The impact of IGS on MAI could be profound. Specifically, IGS has the potential of significantly increasing the user base for MAI by allowing the entire spectrum of the health care community direct and simple access to computing equipment. That is, through IGS, the computer can be made available not only to the experienced physician, nurse or administrator, but to everyone from the low-level clerical assistant volunteer worker to the patient.

There are three aspects of IGS that should be considered in relation to MAI. The first is the development of new programming paradigms that will make IGS more accessible. Object-oriented programming (OOP) is generally regarded as a central isue in the future of graphics and, therefore, IGS. OOP concepts, tools and techniques should be presented in tutorials or introductory programming courses at the university-level for medical and nursing students. In addition, medical computer applications developers should consider using OOP-based programming environments.

The second aspect also involves physicians and computer applications developers. It calls for an extended set of design constructs for medical applications. Current system design approaches call for the logical design of systems based on the specification of input, processing, output and storage modules. The emphasis in the input and output areas is typically on data capture and report generation. The effective use of IGS will require a shift in emphasis to information transfer. That is, designs should focus on how we can better absorb and understand the situation confronting the physician rather than the more clerical aspects of data collection and dissemination. This will require a complete rethinking of many current medical application packages.

The last aspect involves research into the exact mechanisms of graphic information transfer. We are quite knowledgeable about the basic physiology of vision but still very ignorant about the how, what and why of the interpretation of graphic symbols. A great deal of work is yet to be done on how people really absorb and understand graphic information in general, and in particular, for highly stress-intensive situations that often face medical staffs. This basic knowledge can be of great value to MAI and IGS applications.

THE MEDICAL ARTIFICIAL INTELLIGENCE LABORATORY

Strategies for implementing the integration of MAI into the mainstream of clinical medicine must revolve around bringing together clinicians (and medical educators) with computer scientists knowledgeable about AI. In the reality of today's environment, however, any such collaboration must be academically beneficial for both parties. The Medical Artificial Intelligence Laboratory (MAIL) represents an ideal venue for the accomplishment of these goals and objectives.

An effective MAIL must be a multidimensional construct. That is, it must provide an environment for the cross-fertilization of interdisciplinary ideas and expertise. Personnel should be drawn from medical and health care specialists, computer scientists, electronic engineers, mathematicians, and information systems specialists. Interests should range from basic research to applied techniques and technology. The hardware and software tools must be just as broadly-based. The central thrust of the next decade of computer hardware is towards high-end, graphics-oriented workstations, networked to large mainframe systems and specialized I/O units. This hardware direction should be reflected in the MAIL. NEXT computers and RISC workstations will most probably be the computational platforms of choice. However, research in areas like artificial neural systems, vision systems, and natural language translation can be very machine cycle-intensive so that networking to super-computers is a definte requirement.

One picture may or may not be worth 1000 words, but in terms of bits and bytes, a single bit-mapped image using EGA color graphics can require 256 KB. Since physicians are conditioned to visual information transfer, high resolution color displays are absolutely mandatory for medical applications. Therefore, most MAI applications of the next decade will have a strong graphics orientation and massive storage and memories will be needed for the MAIL computer system.

The traditional computer keyboard with its ancient QWERTY key layout, as the major data entry device for the physician, is also an area that requires rethinking in the MAIL environment. Improved input devices that are oriented towards collecting data that the physician uses are in order. For example, the physician collects data on the visual appearance of the patient, and also auditory, thermal and tactile data. We can reasonably expect that if we had those types of data captured by appropriate input sensors, we could extend the range of MAI applications. Therefore, the MAIL computer systems should be flexible enough to accept video images and have sensor-based input systems that can accept audio, thermal and tactile (strain-gage) data.

Effective use of computer systems requires the use of pointing/selection devices like the mouse, rollerball and joystick. Current versions of these devices available for desktop computers are quite crude. They operate in low dots per inch ranges. Development of low-cost, reliable, high resolution pointing/selecting devices is also a precursor for enhanced MAI applications. This is another area for MAIL study.

CONCLUSIONS

Medicine and medical education are changing, and they will continue to do so over the next decade—with or without AI. The challenge facing clinical practitioners, medical educators and computer scientists alike is to establish goals and priorities that will allow MAI to assume a fundamental and positive role in these changes. The generic benefits of AI, particularly in applications involving non-computer-literate users, are clear. The potential for MAI in the next decade is great. To realize this potential will require the close cooperation of physicians and computer scientists alike. An essential component to maximize physician adoption of MAI will be stringent evaluation of MAI systems in prospective trials, combined with greater generalizability than has been evident to date. The analogy to new drug evaluation is clear, and only a logical sequence of design, development, and critical evaluation of emerging MAI technologies will assure widespread acceptance of MAI in the 1990s.

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