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Multidimensional Medical Decision Making

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Abstract – A century ago the physician had too little information on which to determine accurate diagnoses. Due to the rapid progression of technology in the Twentieth Century and the beginning of the Twenty-First Century, this situation changed significantly. Now the physician is faced with multi-parameter analyses that include sophisticated imaging, advanced cardiovascular studies, extensive laboratory tests, and genetic information, all of which impact diagnosis, treatment, and prognosis. New informatics tools are needed to assist, not replace, the physician in the decision process. Decision analysis tools must be flexible to accommodate new methods of diagnosis as well as advances in information technology. In this article, basic structures are defined that can form the basis of such a system.

I. Introduction

Most decision making includes examination of multiple parameters. Along as the number is small, the human decision-making process works well. However, when the number of parameters reaches as little as five the human decision process usually begins to deteriorate [1]. A century ago, the number of parameters involved in medical decision making was limited, due to the lack of information on both diseases and on the state of the patient's health. The body began to give away some of its secrets with the introduction of the radiograph [2] and later the electrocardiogram [3]. With these two devices, the physician was able to make more accurate decisions regarding the presence or absence of some diseases, including pneumonia and cardiac disorders. With the advancement of technology, additional information became available. The simple single radiograph turned into a series of radiographs through the use of CT imaging technologies [4], quickly following by MRI [5], PET [6], and SPECT [7], and more recently by functional MRIs [8] and 4-D imaging to view the beating heart and other conditions based on changes in time [9]. The electrocardiogram also was refined and long-range ECG studies such as Holter recordings [10] became commonplace. Most recently, genetic information has begun to personalize medicine with indications of predisposition to disease based on genetic make-up [11].

Medicine has been faced with many changes over the course of the past decade due to the information explosion. The challenge remains to make full use of this information to benefit diagnosis, treatment, and prognosis. It is not feasible for the human decision maker to adequately deal with all the variables presented by modern medical devices.

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A new paradigm is needed for cooperative medical decision making in which the physician still determines the final decision but is aided by automated methods that reduce and summarize the data items that are available [12]. The basic structure of such a system is described here.

II. Methodology

A. Personal Health Records

Implementation of new methods for analysis of medical data are dependent on data availability and hence on electronic medical records. The ideal goal is the development of a personal health record (PHR) that would trace the medical history of each individual through his or her lifetime. The existence of the PHR would permit analysis not only on current results but also on trends based on temporal analysis using data previously recorded in the PHR [13]. Currently, medical decision making often relies on population statistics to estimate the likelihood of a disease and its progression. Comparisons of lifetime trends for each individual patient would represent a paradigm shift toward true personal healthcare. The overall state of the patient's health is captured as a complex mix of data types. The PHR not only has multivariate numerical components but also information stored as time series (biomedical signals), images, and text. These are all important components for diagnosis and analysis of disease processes; each requires different processing methods.

B. Temporal Database

Figure 1 illustrates the information flow for a patient visit. New data acquired through testing is first analyzed on it own and is then compared to previous data in the PHR to determine patterns. Models are needed for the following:

Data capture and analysis
Identification of specific conditions
Determination of disease status
Evaluation of treatment alternatives

For each visit, values are stored, including tests that are ordered such as laboratory tests, biomedical signals, and imaging.

1. Data Structures

The database comprises a series of vectors that are time-dependent. Complications arise in that many types of data are recorded in addition to numeric values, including images, biosignals, and textual summaries. Each type requires a different method of analysis but all must be combined to form a picture of the state of health of the patient. The following data structures are defined for each test.

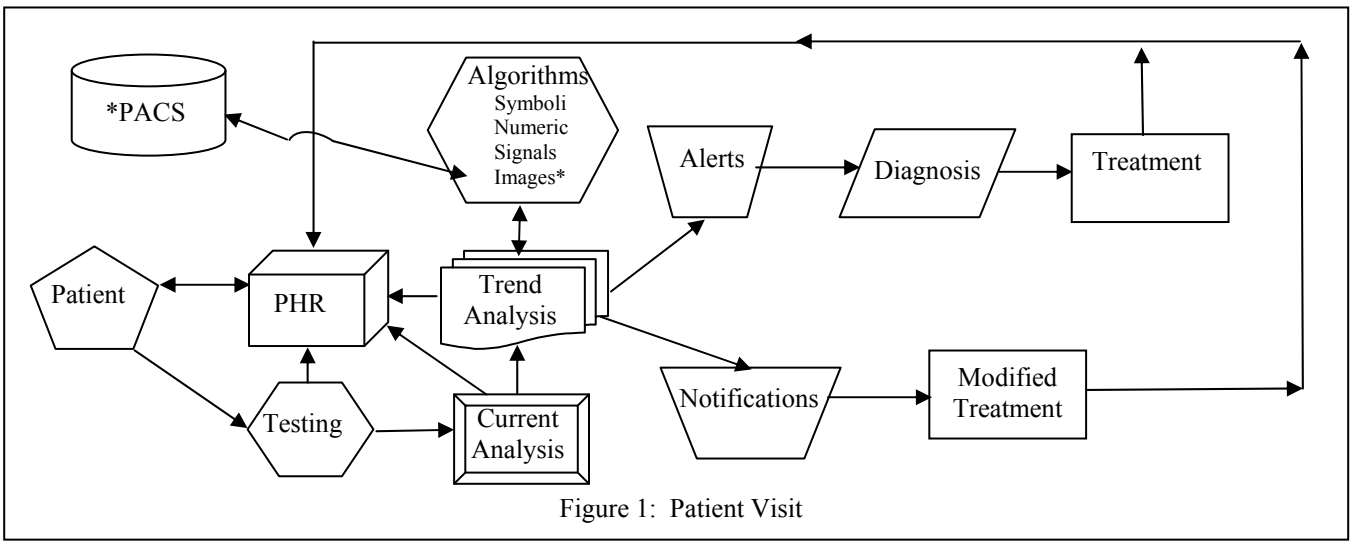

Figure 1: Patient Visit

Numeric Data: For test i that has m numerical values taken at time t:

Numerical data: $\underline{x}_{it} = (x_1,\ldots,x_m)$

Textual Data: Similarly for test j with n textual values:

Textual data $\underline{y}_{jt} = (y_1,\ldots,y_n)$

Signal Analysis Data: Several components are involved:

For text interpretation, the textual data format is used.

For numeric summaries the numeric format is used.

For short-term ECG recordings, the time series itself may be stored, with each series defined by $\underline{s}_{jt} = (s_1,\ldots,s_j)$

(A sampling rate must be established.)

Imaging: Constructing automated image analysis is more complex. For text interpretation, the textual data format is used. More complex information can also be obtained from imaging studies image registration comparisons that may require additional representations in the PHR, although some will be text and some will be numeric. The image component will rely on the PACS architecture [14]. Data structures and interconnectivity links are shown in Figure 2.

2. Disease Models

In order to perform trend analysis, each potential disease must have a model. Some may be quite straightforward, such as the current status of a diabetic patient that may be determined by numeric values from blood tests. Others, such as cardiac disorders, may be complex and require the analysis of multiple data types. Known diagnoses are contained in the vector $\underline{d}$. Each disease model is minimally specified by the following:

Disease name D_i

Tests used to diagnose ($x_1\ldots x_n$; $y_q,\ldots y_r$; $s_i,\ldots s_k$;…)

Type of model(s)

- Knowledge-based
- Data-based
- Hybrid system
- Specialized Data Analysis

C. Trend Analysis

The trend analysis model has four general components:

- Data for current patient visit
- Temporal database
- Disease models
- Trend analysis algorithms

Details of the trend analysis model that involves alerts and notifications have been provided in previous work [15]. Figure 3 shows details of the alerting algorithm. The trend analysis output includes three levels of alerts if a condition has worsened or a new condition is detected. The level depends on the severity of the change or the degree of presence for a new condition:

Level 1: Informational (small negative change)
Level 2: Warning (significant negative change)
Level 3: Urgent (requires immediate action).

Notifications are sent if either of the following is detected:

- Positive change in existing condition
- Complete resolution of existing condition

Development of disease models is multi-faceted and requires interdisciplinary teams to merge medical knowledge with sophisticated automated analysis. Unlike decision support systems of the past, this approach is based on analysis of data, the result of which is presented to the physician in the form of alerts and notifications. The physician makes the final decisions regarding diagnosis and treatment.

In case of missing values, for example consider a patient with a previous blood test that included glucose level, red blood count, and white blood count. If the current test is done without the glucose measure, then an erroneous alert may be issued as the previous value compared to zero would be significant. Missing values must be excluded by not analyzing a vector component with a zero entry. Instead the current value will be analyzed to determine if it is out of the normal range.

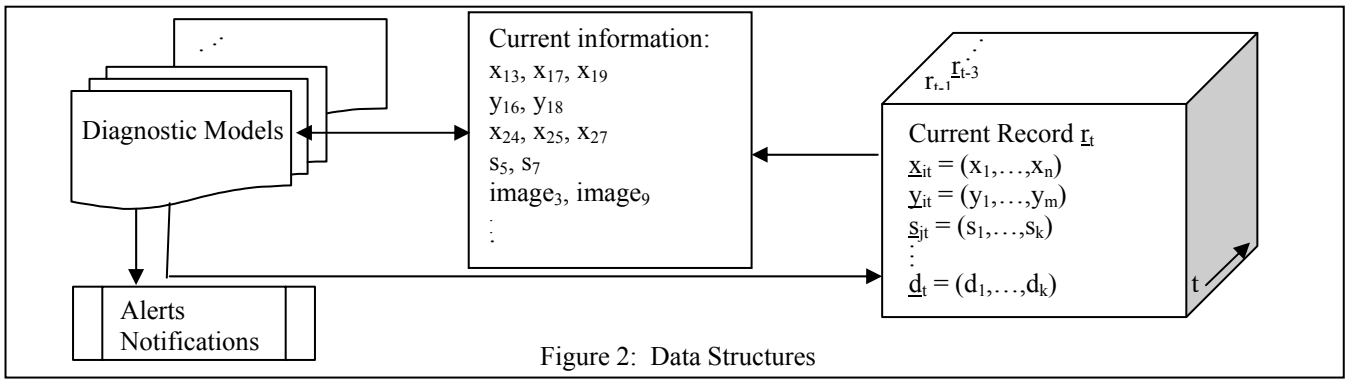

Figure 2: Data Structures

For all currently confirmed conditions
  If condition i is present at time t_n with $\delta(t_n)=a$
    If condition n was previously present with $\delta(t_{n-1})=b$
      set $\alpha = a-b$
    If condition n was not previously present set $\alpha = a$
  If $\alpha > 0$
    if $(x_1 < \alpha < x_2)$ then send alert 1
    if $(x_2 < \alpha < x_3)$ then send alert 2
    if $\alpha > x_3$ then send alert 3
For all previously-confirmed conditions
  If condition is not currently present send notification
    If condition i is present with $\delta(t_n)=a$
      If condition i previously present with $\delta(t_{n-1})= b$
        and if $(b-a) > x$
      then send notification of change in degree

Figure 3: Alert and Notification Algorithm (ANA)
$\delta(t_i)$= degree of presence of condition at time i

III. Example and Results

Consider the following scenario. Patient A has a routine physical. Table I shows the parameters, their current values, values from the previous visit, and the average of five previous visits. In addition, the patient complains of recurring chest pain. Blood pressure and heart rate are elevated and the blood test indcates elevated BUN. All are compared to the immediate previous value and an average of five previous values. Other physical findings include swollen ankles and elevated heart rate. Cardiac problems are suspected. The following algorithms are invoked:

Individual symptom analysis
Symbolic model for symptom evaluation
Summary model for Holter evaluation
Neural network combined model

Table I: Summary of Patient Visit Information

Variable	Current visit	Previous visit	5-visit average
Height	58.5"	59"	59"
Weight	145	140	142
Temperature	37ºC	37.3ºC	37.1ºC
Blood Pressure	180/100	140/95	145/98
Pulse rate	88	80	82
*Holter	CTM 0.79	CTM 0.96	CTM 0.97
*BUN	Elevated	Normal	Normal
*These tests were ordered after the initial analysis			

A. Individual Symptom Analysis

The systolic blood pressure is significantly higher in both comparisons while the diastolic is not significantly higher. Based on the increase in systolic blood pressure, $\delta(t) - \delta(t-1) = 29\%$ and a level 1 alert is issued, following the trend analysis guidelines shown in Table II.

B. Symbolic Model for Symptom Evaluation [16]

Approximate reasoning and evidence aggregation are used to determine rule substantiation. The rule comprises:

a_i: symbolically stated antecedents
w_i: relative importance of i^{th} component
s_i: degree of presence of i^{th} component
T: threshold for rule substantiation.

$$E = \max[(\sum_{i=1}^{n} c_i \wedge s_i) \wedge \min_{i=1,\ldots,n} (w_i^{\,c_i \wedge s_i})] \quad (1)$$

where $\wedge$ indicates min, $c_i \in [0,1]$, n is number of antecedents. The rule is substantiated if $E > T$. The degree to which E exceeds T indicates the strength of the supportive evidence. Thus two types of information are derived:

Substantiation or non-substantiation of the rule
The degree of substantiation defined by:

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

Relevant data for the symbolic model include chest pain and elevated blood pressure. In the absence of other symptoms, no rules in the symbolic database were confirmed. However, a Holter analysis and blood tests were ordered as precautionary measures.

C. Summary Model for Holter Evaluation [17]

A Holter tape consists of a 24-hr recording of R-R intervals (time between heartbeats). For a time series, a_n that occurs at time n, the second-order difference plot is produced by computing a_{n+2}-a_{n+1} vs. a_{n+1}-a_n for all points in the time series. Using this space, points in the time series can be summarized using the Central Tendency Measure (CTM):

Table II: Alert Levels

$\alpha = \delta(t) - \delta(t-1)$	Type of alert
$\alpha \le 0.25\ (1-T)$	No alert
$0.25\ (1-T) < \alpha \le 0.5\ (1-T)$	Level 1
$0.5\ (1-T) < \alpha \le 0.75\ (1-T)$	Level 2
$\alpha \ge 0.75\ (1-T)$	Level 3

$$CTM = [\sum_{i=1}^{t-2} \Delta(d_i)]/(t-2) \quad (3)$$

where $\Delta(d_i) = 1$ if $[(a_{i+2}-a_{i+1})^2+(a_{i+1}-a_i)^2]^{1/2} < r$

$\Delta(d_i) = 0$ otherwise

The model derived through a number of CHF studies shows that for normal individuals the points are centered near the origin (giving a CTM value near 1) while CHF patients have scattering of points with smaller CTM values. Using the CTM as the sole measure, the following can be concluded:

Substantiated if CTM exceeds a threshold;

Certainty increases with an increase in the CTM.

The degree of confidence of the presence of CHF is:

$$\delta(t) = 1 - CTM \quad (4)$$

In this case, the CTM measure was 0.79. The patient had a previous Holter reading of 0.96. Ninety-nine percent of normal patients have a CTM > 0.90 so the new reading triggers a level 1 warning for potential of early-stage congestive heart failure (CHF). To confirm, the more accurate neural network model that includes the CTM measure along with other clinical parameters is run.

D. Neural Network Model Combined Model [18]

The neural network decision equation is:

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

For the vector $\underline{y}$ representing the current case, $D(\underline{y}) > 0$ indicates that the condition is substantiated. The degree of confidence $\delta(t)$ is determined by comparing results from the decision equation $D(\underline{y})$ with $D(\underline{x})$, the decision surface. The further $D(\underline{y})$ is from $D(\underline{x})$ the more certain that the classification is correct. The degree of confidence for this method is thus defined by the normalized value:

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

where z is the vector whose components result in the greatest distance from D(x). Studies have shown that the following parameters are useful for inclusion in the neural network model: CTM (r=0.1), Edema, rales, heart rate, BUN. All $\delta(t)$ values are normalized to the unit interval.

Using the Holter model, a level 1 alert was issued due to the increased scattering of R-R intervals indicating potential early stage congestive heart failure. Combination of these results with the blood tests results in the neural network model triggered a level 2 alert for possible CHF. The values for the current visit along with the diagnosis are added to the patient record. The level 2 alert warrants prescription of appropriate medications as well as follow-up to determine the progression of the condition. Without the final neural network analysis, the level 1 alert would normally warrant monitoring but not necessarily treatment.

IV. Conclusion

The goal of personal health care can only be achieved through the design and implementation of several components [19]. A personal health record that contains all data on the patient for his or her lifetime, including all records from physicians, laboratories, imaging centers, hospitals, and other entities must be available. Universal data collection and access will require international interoperability standards as well as privacy protection [20]. Once the data are available a vast array of diagnostic algorithms will be needed to form a comprehensive view of the state of the patient's health, some of which are mentioned here. Trend analysis can alert the busy health professional to changes and imminent threats that may be buried in a large volume of data. Policy and technology must come together to make personal health care a reality.

References

[1] J Min Park, Online learning by active sampling using orthogonal decision support vectors, Neural Networks for Signal Processing, Proceedings IEEE APS Workshop, 10(1):195-2003, 2000.

[2] H Mann, A lightweight portable EKG, Am. Heart J., 7:796, 1930-1931.

[3] E Tragardh, TT Schlegel, High-frequency QRS electrocardiogram, Clin. Physiol. Funct Imaging, 27(4):197-204, 2007.

[4] GN Hounsfield, Computerized Transverse Axial, Scanning (Tomography): Part 1. Descrip. System, Br. J. Radiol, 46:1011, 1973.

[5] LE. Crooks, Selective irradiation line scan techniques for NMR imaging, IEEE Trans. Nucl. Sci., NS-27(3), 1980.

[6] TM Guerrero, EJ Hoffman, M Dahlbom, et al., Characterization of a whole body imaging technique for PET, IEEE Trans. Nucl. Sci., NS-37:676-680, 1990.

[7] RJ Jaszczak, LT Chang, PH Murphy, Single photon emission computed tomography using multi-slice fan beam collimators, IEEE Trans Nucl Sci, NS-26:610-618, 1979.

[8] M Brett, IS Johnsrude, AM Owen, The problem of functional localization in the human brain, Nature Rev. Neurosci., 3:243-249, 2002.

[9] WP Segars, M Mahesh, TJ Beck, EC Frey, Bm Tsui, Realistic CT simulation using 4D XCAT phantom, Med. Phys., 35(8):3800-8, 2008.

[10] ME Cohen, DL Hudson, PC Deedwania, Measurement of variability in Holter tape R-R intervals for patients with congestive heart failure, Conf Proc IEEE EMBS, 16:127-128, 1994.

[11] H Tanaka, Bioinformatics and genomics for opening new perspective for personalized care, Stud Health Technol Inform., 134:47-58, 2008.

[12] DL Hudson, ME Cohen, Cooperative Medical Decision Support, World Congress on Computer Sci. and Information Engr., 2:373-376, 2009.

[13] DL Hudson, ME Cohen, Technologies for Patient-Centered Healthcare, IEEE-NIH Life Sci. Sys. Appl. Workshop, 2:203-206, 2007.

[14] A Shullman, PACS/RIS/imaging. Radiology's golden age. RIS/PACS automation, Health Manag Technol. 30(2):12-3, 24, 2009.

[15] DL Hudson,ME Cohen, Temporal Trend Analysis in Personal Health Records, Conf Proc. IEEE EMBS, 30:3811-3814, 2008.

[16] DL Hudson, ME, Cohen, An approach to management of uncertainty in an expert system, Int. Journal of Intelligent Systems, 3(1):45-58, 1988.

[17] ME Cohen,DL Hudson, New Chaotic Methods for Biomedical Signal Analysis, IEEE EMBS ITAB, 117-122, 2000

[18] DL Hudson, ME Cohen, Neural Networks and Artificial Intelligence in Biomedical Engineering, IEEE Press/Wiley, 1999.

[19] Y Denekamp, Clinical decision support system for addressing the information needs of physicians, Isr Med Assoc J, 9(11):771-6, 2007.

[20] J Glaser, DE Henley, G Downing, KM Brinner, Advancing Personalized Health Care Through Health Information Technology: An Update from the American Health Information Community's Personalized Health Care Workgroup, J Am Med Inf. Assoc, 15(4):391-6, 2008.