Confidence Levels for Medical Diagnosis on Distributed Medical Knowledge Nodes

NARONGRIT WARAPORN
School of Information Technology
King Mongkut's University of Technology Thonburi
126 Pracha-U-Thit Rd., Bangmod, Thungkru, Bangkok 10140
THAILAND
http://www.sit.kmutt.ac.th/narongrit/

Abstract: - This paper presents the methodology of defining the confidence levels for computer-aided medical diagnosis according to the patient-doctor visiting. It is a part of on-going research in the Medical Knowledge Technology (MKT) system. With the expansion of medical knowledge into the Internet by various groups of Tele-medicine researchers, the suggestion of confidence levels for medical diagnosis on multiple medical knowledge nodes of the distributed databases, as simultaneously consulting doctors, is presented. The extension of this AI methodology to in the medical field via Internet will provide support to the physicians and improve the health of world population.

Keywords: Confidence levels, Computer-aided medical diagnosis, MKT, Internet, Tele-medicine, Knowledge nodes, Distributed databases, AI.

1. Introduction

Since 1970's when the computer systems have been adopted by various groups of developers, the medical application was one of the major development to provide better health to mankind. [18] and [15] were the early pioneers in computer-based medical consultants. They have been stretched out to many perspectives including, recently, the investigation of [17] to mining medical and clinical data for knowledge discovery.

The structures of application on Tele-medicine Systems (TS) have been defined by many researchers; ELMP in [13] based on real evidence of medical practice, MA-DCA in [9] using hybrid systems to express evolution models, logic models, interface between them, behavior requirements and real time constraints, Fuzzy Neural Network in [6] for the decision making in the treatment of duodenal ulcer, WebMIA in [21] using modality-dependent toolboxes to engage online document processing and PoRDITS in [11] using DICOM3 to support medical communication.

By the same time, the medical knowledge is classified into four sets [20], absolute, trusted, unconfirmed, and misconduct facts extended from three fuzzy sets of knowledge in [10] and two quantitative fuzzy and nonfuzzy sets in [6] whereas [8] and [12] classified the medical terminology using forest hierarchy and Medical Concept Mapper sequentially.

Many medical diagnostic applications [4] , [5], [14] use such medical knowledge to support physicians by means of accurately evaluation by using computer systems while HCW prototype in [16] described the reduction of the medical errors based on the rules of abstract analysis.

In this paper, we present an approach to the confidence level of medical diagnosis on medical knowledge according to our Medical Knowledge Technology (MKT) system. We present the layers of medical deduction in section 2 and definability of confidence levels on a medical agency in section 3. While [19] used Metastatistical analysis of temporal data to develop methods for multilevel processing on medical data, this paper defines the confidence levels for the multiple medical agencies in section 4 which is more mathematically specific comparing to the [1] and [14].

2. Layers of Medical Deduction

Confidence level is the probability value associated with confidence interval given an estimated range of values which is likely to include an unknown population parameter, the estimated range being calculated from a given set of sample data [3]. Confidence estimation is a technique for assessing the quality of a particular prediction that may be used to improve branch prediction rate [7] for each layer in our system and any MSP's of [2].

Before we define the values of confidence levels using in our system, we present three layers and conclusion of medical care process [5] in our system.

Layer 1 Receiving the symptoms [14] from a patient. Number of symptoms from patient is depending on how the patient is conscious of unusual occurrence to his health. At the first step of medical examinations, the patient will notify by him/her self. We called this layer "Patient Symptoms".

Layer 2 However there are symptoms that may occur unnoticed to the patient. The medical expert must gather the other symptoms from the likely illnesses whose symptoms were given at the first step. We call this layer "Mark Symptoms". The deduction of finding the right illness starts at this layer. The following are different deductive algorithms:

- If symptoms of a disease A, given by the medical expert, are not recognized by the patient, the second list of symptoms from disease B will be asked and so on for disease C, D, etc. This algorithm is considered one disease at a time.
- The second algorithm is considered all likely illnesses, whose symptoms were matched with first step, together. The common symptoms of all (or most amount of) diseases will be asked first. If one or more of the given symptoms occurs to the patient, other illnesses that does not have these symptoms will be eliminated from the choice of likely diseases. However, if these common symptoms do not occur to the patient, these diseases, having these common symptoms, will be eliminated and then the second, third, and lower common symptoms will be asked. The worst deductive case is that patient has a few and rarely occurring symptoms. This deductive step might be time-consuming for this worst case. However, because of the rarely occur and uncommon symptoms, it is a very small chance that this algorithm will reach the worst case. However, if the reported symptoms occur very frequently, the deductive process in this algorithm will probably find the likely illness faster than the other algorithms.
- The third case is the combination of the first and second algorithms. The medical expert shows all symptoms together, not once at a time as in the second algorithm, but the order of symptoms is starting from the most common occurring symptom to the least common occurring symptom. There is no switching page-by-page for user's intolerance and reduce processing time by the program to deductively reevaluate for each symptom when there are lots of symptoms that may occur to the patient. Therefore, as for this research, we choose this algorithm in our testing programs.

Layer 3 Before the conclusion, the cause of illnesses can be used for deduction. Similar to the layer 2, the cause of illness may be unnoticed to the patient. Therefore, the previous three algorithms can be used to find out about the cause(s) of patient's illness. As for simplicity, the third algorithm is used in our system. However, the cause list will not be ordered by the commonality of causes, as symptoms in the second layer. Because the deductive medical analysis of occurring symptoms was evaluated in the second layer, it will be ordered by the likeliness of illnesses to the patient.

Conclusion After the last layer, the patient will be given the conclusion of the examination and so we called it "Disease Conclusion". Generally, final goal of visiting medical expert of a patient is to receive medical advice including method of treatment, health and life-style adjustments, etc. Mostly, the medical expert may give the medical prescription to the patient. Most physicians will prescribe the standard medical treatment, which medical experts generally agree is best. However, in some cases, for diseases that are not well understood, it may be useful to consider alternative treatments. These could be treatments for which there is preliminary evidence that they are beneficial, but the evidence is not yet conclusive, so the treatment is not considered part of standard treatment. The Internet can be useful in identifying such alternative treatments and the evidence to support their merits. (Unfortunately, sometimes the Internet is used by dishonest people who try to promote ineffective treatments to people who have incurable illnesses.) Therefore, many medical computerized experts over the Internet only show the types of medicine and method of remedy suitable to the patient but do not prescribe the medical prescription.

3. Confidence Levels on Single Medical Agency

The confidence levels are defined after each layer of the medical deductive process. As for our system, we distribute the medical knowledge in multiple databases. For simplicity, the confidence levels are, first, defined for only one source of medical knowledge. For multiple sources, the confidence levels are defined in the next section.

After Layer 1 At the first layer, we give a 50% confidence level for the one medical knowledge database. These 50% will be comprehensively defined later at the multiple medical knowledge databases. Because we divide the medical examination into three layers, confidence level of the higher layer is one-sixth higher, ⅓ of 50% = 1/6. Therefore, after the first layer, the constant ratio of the confidence level is 50% + 1/6 = 4/6.

Let α be the number of patient symptoms, β be the number of diseases having patient symptoms, i be the number of spaces given to the patient and CL be the confidence level.

The larger the number of symptoms reported by the patient, the better the analysis leading to a conclusion. The second factor is the ratio between the known symptoms by the patient, α, comparing to the number of allowed inputs, i, given to the patients. For example if a physician asks "Give me five symptoms", then i is 5. The i could be any number that a patient could reasonably be expected to report. As for our system, i is 3.

The third factor is the number of diseases, β, having all patient symptoms. The highest confidence level is when β is 1, on which only one disease has all patient symptoms. The confidence is less when more diseases return from the query.

Therefore, at the first layer, the confidence level, CL is

$$CL = (50\%) + ((1/3)*50\% * (\alpha / i) * (1/\beta))$$

$$CL = (3/6) + (1/6 * (\alpha / i) * (1/\beta)) \quad (1)$$

After Layer 2 At the second layer, the constant factor is one-third higher, ⅔ of 50% = 2/6, from the first layer because of three-layer methodology. Therefore the constant ratio of confidence level at the second layer is 50% + 2/6 = 4/6.

At the second layer, the patient is given n choices of symptoms of disease related to patient symptoms given in the first layer by the patient. If the patient recognizes other symptoms from the list, the confidence level will be higher. The number of new symptoms recognize by the patient is θ.

We separate the confidence level into two sets, the confidence level of each disease and the overall confidence level. The confidence level of each disease in the second layer is factored by the ratio between all the known patient symptoms including symptoms in both first, α, and second, θ, layer, and the all symptoms, n, of the disease, $[\alpha + \theta] / n$.

The third factor, applied only to the overall confidence level, is the number of diseases, β, but is not applied in the same approach as in the first layer. It is applied for the average of the confidence levels of all diseases.

Therefore, at the second layer, the confidence level of each disease i, CLD_i is

$$CLD_i = (50\%) + ((2/3)*50\% * ([\alpha + \theta] / n_i))$$

$$CLD_i = (3/6) + ((2/6) * ([\alpha + \theta] / n_i)) \quad (2)$$

where α is the number of patient symptoms in the first layer,

θ is the number of patient symptoms recognized from the list in the second layer,

n_i is the number of choices of all symptoms of a disease i showing to the patient as a list,

and CLD_i is the confidence level of each disease i.

The overall confidence level, CL, of the second layer is

$$CL = (CLD_1 + CLD_2 + CLD_3 + \ldots + CLD_\beta) * (1/\beta)$$

$$CL = (\sum_{i=1}^{\beta} CLD_i) / \beta \quad (3)$$

where CLD_1, CLD_2, CLD_3, … , CLD_β are the confidence levels of all diseases having patient symptoms.

After Layer 3 At the layer 3, the causes of all related diseases are shown. The patient chooses his/her cause(s) recognized from the list. The causes are used for illness(s) inference together with the symptoms given in the first and second layers. If there is only one disease corresponding to the symptoms and causes, then the confidence level, whose value between 0 and 1, is 1.

If there are two or more diseases matching the symptoms and causes of the patient, then confidence of each disease i is delineated by two factors the symptoms and causes. The symptoms weight 2/6 as in the second layer and the causes weight the rest, 1/6. The cause factor is the ratio between the number of causes recognized by the patient, σ_i , (after the doctor reminds the patient of what the patient may have done in the past) of the disease i and the number of causes, m_i, of disease i. Because the patient is likely to recognize only one or few causes, the cause factor is logarithm ratio, $\log_{mi} \sigma_i$. First known cause is worth more than second cause, and so on.

The cause factor is logarithm of ($\sigma_i + 1$), not logarithm of σ_i. σ_i is added by 1 because when $\sigma_i = 1$, $\log_{mi} 2$ is not 0. If it is not added by 1 when $\sigma_i = 1$, $\log_{mi} 1$ is 0, which means the one cause does not effect to the confidence level which is not possible. Because of 1 is added to σ_i, m_i must be added by 1 to accommodate when $\sigma_i = m_i$. Therefore the cause factor after the third layer is $\log_{mi+1} (\sigma_i + 1)$

The overall confidence level is the average of confidence levels of all corresponding diseases. For the case that patient does not input any cause, the confidence level remains as in the second layer.

Therefore, depending on the number of diseases having patient symptoms and cause(s), $\beta2$, the overall confidence level, CL, for the conclusion is

If $\beta2 = 1$ then

$$CL = (5/6) + (1/6) = 1$$

Else if $\beta2 > 1$ then

$$CLD_i = [3/6] + [(2/6) * ([\alpha + \theta] / n_i)] + [(1/6) * \log_{m+1} (\sigma_i + 1)]$$

$$CL = (CLD_1 + CLD_2 + \ldots + CLD_{\beta2}) * (1/\beta2) + (CLD_{\beta2+1} + CLD_{\beta2+2} + \ldots + CLD_{\beta}) * (1/\beta1)$$

$$CL = (\sum_{i=1}^{\beta} CLD_i) / \beta$$

Otherwise (when $\beta2 = 0$)

$$CLD_i = (3/6) + [(2/6) * ([\alpha + \theta] / n_i)] + 0$$

$$CL = (CLD_1 + CLD_2 + \ldots + CLD_{\beta1}) * (1/\beta1)$$

$$CL = (\sum_{i=1}^{\beta1} CLD_i) / (\beta1) \quad (4)$$

where α is the number of patient symptoms in the first layer,
$\beta1$ is the number of diseases having patient symptoms but not cause(s),
$\beta2$ is the number of diseases having patient symptoms and cause(s),
$\beta = \beta1 + \beta2$,
σ_i is the number of patient cause(s) for disease i,
m_i is the number of cause(s) for disease i,
and CLD_i is the confidence level of each disease i.

4. Confidence Levels on Multiple Medical Agencies

There are three situations of agreement when multiple agencies, which are knowledge sources in our system, coordinate the deductive process.

- **Complete Agreement** All agencies agree on the same conclusion. As for our research, all multiple medical sources agree on the same disease for conclusion.
- **Partial Agreement** Some agencies, but not all, agree on some conclusions, and also some agencies do not agree on some conclusion.
- **Complete Disagreement** Conclusion of each agency has not agreed with the conclusion of any other agencies.

Using the number of agencies who agree (and do not agree), we can define the CL's on multiple medical agencies in the following steps.

After Layer 1 The confidence level for the multiple medical sources is the extension of the first 50% (or 3/6) factor of the confidence level in the layer 1 of the single medical agency. It is also divided by 3 into three layers. Therefore, in layer 1 of multiple agencies, it is one-third of 50% = 1/6. If all knowledge sources agree on the same conclusion, the 50% factor of confidence level remains the same as of single agency.

$$CL = ((⅓)*50\%) + ((⅓)*50\%) * (\alpha / i) * (1/\beta))$$

when all agencies agree on all diseases.

If none of conclusion of any agency agrees with others' conclusion, then 50% is discarded.

$$CL = 0 + ((⅓)*50\%) * (\alpha / i) * (1/\beta))$$

when no agreement at all.

In the case that there is agreement on some conclusion(s), the 50% factor is rationalized by the ratio of the amount of agreeing sources to the amount of all knowledge sources.

$$CL = [(⅓)*50\% * \lambda/s] + [(⅓)*50\% *(\alpha / i)*(1/\beta)]$$

when some agencies agree on all diseases,
where λ is the number of sources agreeing,
and s is the number of all knowledge sources.

The case of some agreement can be generalized for the cases of all sources and no source agreeing. Therefore, the generalized term of confidence level for the level 1 is

$$CL = [(⅓)*50\% * \lambda/s] + [(⅓)*50\% *(\alpha /i)* (1/\beta)]$$

$$CL = [(1/6) * \lambda / s] + [(1/6) * (\alpha/i) * (1/\beta)] \quad (5)$$

where α is the number of patient symptoms in this layer,
i is the number of choices given to the patient,
λ is the number of sources agreeing,
and s is the number of knowledge sources.

After Layer 2 At the second layer, the factor of multiple sources becomes two-thirds of 50%, that is 2/6. Similar to the single source, the confidence level at this layer of multiple sources is, still, separated by each disease, and the average of confidence levels of all diseases is the overall confidence level. However, because of multiple sources, confidence level of each disease must be categorized for each knowledge source. Two methodologies are proposed, the classification by diseases of each knowledge source, and the agreement of sources on each disease.

- The classification by diseases of each knowledge source defines the confidence level of each disease in same way as of the single source but for each source.

$$CLD_i S_j = (2/6) + [(2/6) * ([\alpha + \theta] / n_i)] \quad (6)$$

where $CLD_i S_j$ is the confidence level of each disease i for each source j.

The confidence level of all diseases of source S_j, CLS_j, of this layer is the average among the diseases of the same source j.

$$CLS_j = (\sum_{i=1}^{\beta} CLD_iS_j) / \beta \quad (7)$$

The overall confidence level CL, of the second layer for the classification by sources is the average among all knowledge sources.

$$CL = \left(\sum_{j=1}^{s} CLS_j\right) / s$$

$$CL = \left(\sum_{j=1}^{s} \left[\sum_{i=1}^{\beta} CLD_iS_j\right] / \beta\right) / s \qquad (8)$$

where β is the number of diseases having patient symptoms,
s is the number of knowledge sources,
and CLS_j is the confidence level of each source j.

- The agreement of sources on each disease rationalizes the two-third of 50% factor by the ratio between the number of agree sources and the number of all sources. Similar to the first layer but defined for each disease, the two-third of 50% factor remains for conclusion of agreement of all sources, and the two-third of 50% is discarded for a case of no agreement, only ratio of symptoms. Therefore, the confidence level of each disease for multiple sources and the overall of the confidence level are:

$$CLD_i = [(2/6)*(\lambda_i / s)]+[(2/6) * ([\alpha + \theta] / n_i)] \qquad (9)$$

$$CL = \left(\sum_{i=1}^{\beta} CLD_i\right) / \beta \qquad (10)$$

where λ_i is the number of sources agreeing on symptoms for disease i.

The first methodology is much simpler to implement because there is no synchronization among sources for each disease but less accurate than the second methodology. Confidence level is defined primarily for each source, not each disease at the first methodology. Therefore, we choose the first methodology in our system for the simplicity.

After Layer 3 The third portion of 50% factor is considered in the layer 3 for the multiple agencies. As for our system, it is the factor of patient's causes whether they are agreed on multiple sources. Therefore, the third portion of 50% factor is rationalized by the ratio of the number of agreeing sources on user cause(s) to the number of all sources. Other factors of confidence levels remain the same as in the single knowledge source.

Therefore, the overall confidence level, CL, for the agreement of sources on each disease (the 2nd methodology of the layer 2) at the conclusion is

If $\beta2 = 1$ and $\lambda2_i = s$ then

$$CL = (5/6) + (1/6) = 1$$

Else if $\beta2 > 1$ then

$$CLD_i = [(2/6) * (\lambda_i / s)] + [(1/6) * (\lambda2_i / s)] +[(2/6)*([\alpha + \theta] / n_i)] + [(1/6)*\log_{(mi+1)} (\sigma_i + 1)]$$

$$CL = (CLD_1 + CLD_2 + \dots + CLD_{\beta2}) *(1/\beta2) + (CLD_{\beta2+1} + CLD_{\beta2+2} + \dots + CLD_{\beta})*(1/\beta1)$$

$$CL = \left(\sum_{i=1}^{\beta} CLD_i\right) / \beta$$

Otherwise (when $\beta2 = 0$ and $\lambda2_i = 0$ of all sources)

$$CLD_i = (2/6 + 0) + [(2/6) * ([\alpha + \theta] / n_i)] + 0$$

$$CL = (CLD_1 + CLD_2 + \dots + CLD_{\beta1})* (1/\beta1)$$

$$CL = \left(\sum_{i=1}^{\beta1} CLD_i\right) / (\beta1) \qquad (11)$$

where $\lambda2_i$ is the number of sources agreeing on symptoms and cause(s) for disease i.

For the first methodology of the second layer that defines CL's for each source to reduce the cost of synchronization among knowledge nodes in our system, we define the CLD_i's for each source and the overall CL as:

$$CLD_iS_j = [(3/6)] + [(2/6) * ([\alpha + \theta] / n_i)] + [(1/6) * \log_{(mi+1)} (\sigma_i + 1)]$$

$$CLS_j = (CLD_1S_j + \dots + CLD_{\beta2}S_j) * (1/\beta2) + (CLD_{\beta2+1}S_j + \dots + CLD_{\beta}S_j) * (1/\beta1)$$

$$CL = \left(\sum_{j=1}^{s} CLS_j\right) / s$$

$$CL = \left(\sum_{j=1}^{s} \left[\sum_{i=1}^{\beta} CLD_iS_j\right] / \beta\right) / s \qquad (12)$$

5. Future Research

For future research, the CLs can be enhanced by:

- Influence factor for causes may have weight factor scale between, let us say, 1 to 5 depending on the commonality of occurrences among patients or among diseases.
- Influence factor for symptoms that can split into two levels, user symptoms and database shown symptoms. Each level may have a different weight value of factor.
- Other data such as direct detector, or bio-chemical check-up in the second and third ordered information of [14], can strengthen the CL's.

6. Conclusion

Applying confidence level to medical diagnosis improves the dependability of the medical expert system to its users including medical researcher, physicians, and patients for every phase or every decision point in the medical analysis and for the overall procedure. It can also provide automating the medical analysis over the Internet to expand medical expertise to serve the needs of developing and undeveloped countries where improvements in healthcare are urgently needed.

Because our confidence levels are defined for multiple sources, our methodology can be used for systems that maintain synchronizing knowledge nodes such as homeland security coordination and natural disaster prediction and preparation.

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