

Applying Case Based Reasoning System in the Treatment Decision of Gynecological Disorders: Fibroid

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------ABSTRACT------

Uterine fibroids are benign growths in the uterus, for which there are several possible treatment options. Patients and physicians generally approach the decision process based on a combination of the patient's degree of discomfort, patient preferences, and physician practice patterns. A Physician's decisionmaking skills are directly related to the patient's positive outcomes. Therefore, a wealth of medical knowledge and clinical experience are key assets for a physician to have. The goal here is to use historical clinical data and relationships processed by Artificial Intelligence (AI) techniques to aid physicians in their decision making process. The System provides a large number of medical support functions to help clinician choose the best treatment measures. This paper presents case based approach to fibroid treatment decision. Both inductive indexing and nearest neighbor technique are involved in case retrieval phase. In this paper, Local similarity measure is applied to find the similarity between features while global similarity measure is applied to find the most similar case.

Keywords: Global similarity, Inductive indexing, Nearest neighbor, Uterine Fibroid, Uterus,

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I. INTRODUCTION

Uterine fibroids are benign growths of smooth muscle cells and fibrous tissue in the wall of the uterus. Approximately 30% to 40% of women of reproductive age are affected by uterine fibroids. Over 50% percent of these women report symptoms that affect their quality of life, such as heavy bleeding, anemia, pelvic pain, pelvic pressure, urinary problems, pain during intercourse, bleeding between periods, and infertility among others [1]. Knowing the types of fibroids and the associated symptom is important in deciding the type of fibroid treatment that will be the best option for you and your lifestyle. Among the various types of fibroid tumors are submucosal, intramural, subserosal fibroids and pedunculated fibroid tumors. Surgical options such as hysterectomy and Myomectomy have been the mainstay of fibroid treatment. Hysterectomy is the surgery that removes the uterus completely which results in permanent loss of reproductive potentials, while Myomectomy is the surgical removal of the fibroid retaining the uterus, but with high failure rate and high rate of fibroid re-growth. These treatment options typically result in 5-7 days of hospitalization, very expensive, high blood loss which eventually leads to blood transfusion. Given the substantial impact of surgery, minimally invasive procedures have been developed, such as uterine fibroid/artery Embolisation (UFE)/ (UAE). This technique for the treatment of uterine fibroids was first performed by Ravina, a French gynecologist, in 1995 [2]. UFE may require a few hours hospital stay. Sideeffects and complications are few. Studies have shown that risks and complications are significantly lower than surgery. Many women resume light activities in a few days, and a majority of women return to normal activities within three to seven days. For the successful performance of this procedure, experience is important. The most experienced physicians performing UFE will provide you the best pre and post UFE care, as well as the most durable results. With Uterine Artery Embolisation (UAE), it is only in extreme conditions that Hysterectomy is recommended for patient despite the patients' age. Myomectomy will be an option when a patient strongly desires to have children and should be followed by UFE thereafter because there is always high probability of Fibroid re-growth. Though there are proven cases of women that have conceived after UFE but due to the fact that the ovaries are exposed to Radiation, the possibility of this exposure having side effect to a woman's ability to conceive has been under researched.

Computer aided approach to fibroid treatment decision is described. Simplified case based reasoning software has been developed to assist clinicians in helping their patients in taking the right fibroid treatment decision. Fibroid cases are very common and serious cases among women especially those of child bearing age. Many today are facing the ugly psychological and medical effect of having what makes them a woman (ovaries & fallopian tube) removed. Many doctors convince their patients who have passed that they "no longer need the uterus". Those who have once had the fibroid removed maintaining their uterus due to their choice of having more pregnancies are now living with more fibroids that have re-grown since they might not have Myomectomy performed a second time. Many surgeries performed on women living with fibroid today in Nigeria were not necessary because their conditions would have been taken care of with UFE. Different approaches to aid doctors and patients in making the best treatment decision have attracted serious research attention in recent times. The essence of these approaches is to achieve high performance treatment. Obviously it is difficult to take a treatment decision based on personal experience or misguided anecdotal evidence. Treatment decisions are usually based on several conditions, which include: severity of the condition, age, location and size of the fibroid, other medical history, and patients' choices. These conditions must be satisfied before an efficient treatment decision is made. Going by the complexities experienced by both physicians and patients, there is need for an efficient treatment decision approach which will be based on the cumulative experience of all the patients with fibroid cases and the best treatment each case received, stored in a large medical database.

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1.1 Purpose of the Paper

The aim of this paper is to present a case based approach to treatment decision for Fibroid patients.

1.3 Case-Based Reasoning Technique

Case-based reasoning is both an artificial intelligence methodology and a cognitive model of reasoning such that reasoning is inseparable from memory and from learning. This cognitive model is a very high aim, which current case-based reasoning systems are just beginning to pursue. The tight interaction between reasoning, memory and learning is one characteristic of the general description of the system. The main steps in the reasoning process are to retrieve, to reuse, to revise and to retain.

1.3.1 Retrieve:

The Retrieve task starts with a (partial) problem description and ends when a best matching previous case has been found. This matching process is directed by the task to perform. Its subtasks are referred to as Identify Features, Initially Match, Search, and Select, executed in that order. The identification task basically comes up with a set of relevant problem descriptors, the goal of the matching task is to return a set of cases that are sufficiently similar to the new case - given a similarity threshold of some kind, and the selection task works on this set of cases and chooses the best match.

1.3.2 Reuse:

This step is very dependent on the task performed. In problem-solving, it is an adaptation of the most similar case solution to fit the new case. In other tasks, such as interpretation, it can be the construction of an argumentation linking the new case with the retrieved cases. The reuse of the retrieved case solution in the context of the new case focuses on two aspects: (a) the differences among the past and the current case and (b) what part of a retrieved case can be transferred to the new case. In simple classification tasks the differences are abstracted away (they are considered non relevant while similarities are relevant) and the solution class of the retrieved case is transferred to the new case as its solution class. This is a trivial type of reuse. However, other systems have to take into account differences in (a) and thus the reused part (b) cannot be directly transferred to the new case but requires an *adaptation* process that takes into account those differences.

1.3.3 Revise:

Depending on the success or the failure of the new case processing, the reused case is revised and transformed into an updated case, now ready to be stored in the memory. When a case solution generated by the reuse phase is not correct, an opportunity for learning from failure arises. This phase consists of two tasks: (1) evaluate the case solution generated by reuse. If successful, learning from the success, (2) otherwise repair the case solution using domain-specific knowledge.

1.3.4 Retain:

This is the process of incorporating what is useful to retain from the new problem solving episode into the existing knowledge. Case retention not only directly relates to the difficulty of the case base maintenance, but also affects the reasoning efficiency and correctness of the CBR system [3]. Learning from success or failure of the proposed solution is triggered by the outcome of the evaluation and possible repair. It involves selecting which information from the case to retain, in what form to retain it, how to index the case for later retrieval from similar problems, and how to integrate the new case in the memory structure. The algorithm performing this can be given as; *Insert (Trend, Case)* [4].

Below is a schematic cycle of CBR process;

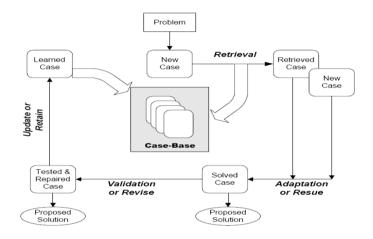


Figure 1, CBR cycle

A new framework for constructing alternative knowledge base in case based reasoning system based on rough sets and formal concept analysis was proposed by [5]. Their framework first applies rough set theory for discovering reduced cases required in a case based reasoning system. Then a hierarchical structure of knowledge base using formal concept analysis is achieved. The result is the concept lattice knowledge base embedded to our proposed case based reasoning system.

II. RELATED WORK

Case based reasoning is sometimes combined with other models to produce more accurate result. CBR are often combined with Fuzzy model, rule based among other models. Such combination serves as mechanism of matching between cases. In Recommender systems, collaborative filtering technique has been proved to be one of the most successful techniques [6]. Recommender system uses recommendation algorithm that combine the case-based reasoning and item-based collaborative filtering. The purpose of this combination is to alleviate sparsity issue and to produce more accurate result. HCBR (Hybrid case based reasoning) incorporates an RBR (Rule based reasoning) sub-system to compensate for the major disadvantages of CBR, that is poor indexing and locating of similar cases [7]. Moreover, the RBR sub-system has standard sets of rules that can be applied when there is no similar case in its case database. The ability of a CBR system to learn from its previous experience enhances the accuracy of the recommended solutions as time goes on.

In collaborative design, there is always a problem of conflict resolution. [8] Proposed a fuzzy CBR method. The fuzzy CBR method is presented to solve the problem of conflict resolution in collaborative design, which can find the similar case from database to solve the problem. Based on the feature attributes and their relative weights determined by a fuzzy technique, a fuzzy CBR retrieving mechanism is developed to retrieve conflict resolution cases that tend to enhance the functions of the database. The theory and methods of fuzzy CBR is applied to define the cases. By indexing, calculating the weight and defuzzication of the cases, the case similarity can be obtained. Then the case consistency is measured to keep the result right. Finally, the method is demonstrated availably for conflict resolution by means of a case study.

[9] Proposed a fuzzy case-based reasoning. In this rule, fuzzy rule based reasoning serves as a mechanism for matching between cases. The key concern is to determine which kinds of cases should be considered as "similar" given a new case which is problem and domain dependant.

Case searching efficiently is an important challenge because case retrieval is a time-consuming process. It is a central part of CBR and has a great impact on the efficiency of the system. In "fixture design", [10] proposed combining both case based and rule based reasoning technique to eliminate the drawbacks of each method and provide a better way for fixture design. [11] Proposed the combination of both case based and rule based technique in fire fighting tactics to extract a new happened accident characteristics, calculate the similarity degree and characterize different firefighting accidents. The augmentation of Rule Based System with Case Based Reasoning allows us to handle exceptions gracefully, without making a rule set overly complicated [12].

[13] Presented a benign/malignant breast cancer classification model based on a combination of ontology and case-based reasoning to effectively classify breast cancer tumors. Two CBR object-oriented frameworks based on ontology were used, *jCOLIBRI* and *myCBR*.

III. SUBJECTS AND METHODS

The case-based reasoning system will function as a database query of Fibroid cases with known treatment outcomes. When a new case (called a "test case") is considered for treatment decision, the system will match the test case to the entire database. The system returns the values of cases that match. This value serves as an indicator for treatment decision.

The critical components of the case-based reasoning system will be as follows:

- i. A translatable quantitative encoding for cases,
- ii. A database of cases,
- iii. A rule to define when the test case matches a case in the database.

The input to the system is diagnosis result, items from the patients' medical histories and patient's choices. The output is formed from the known outcome of treated cases stored in the data base. The database will consists of a set of medical history, set of patient's choices, and a set of diagnostic results for cases that were treated with Hysterectomy, Myomectomy, and UFE. The heart of the system will be the set of rules defining a match between the test case and the known cases in the database. The trivial match criterion would be that all findings match exactly. Cases are matched if they are "close" in some sense.

3.1 Applying both Inductive Indexing and Nearest Neighbor Technique in Case Retrieval Phase

To retrieve a set of matching cases, inductive indexing will be used, and then nearest neighbor will be used to rank the cases in the set according to the similarity to the target case. The system will perform both Local and Global similarity measure.

Local similarity measure finds the similarity between each feature of the new case and existing cases. The computation of the global similarity will be based on the local similarity values computed previously and the attribute weights. The system will perform the global similarity measure for case into a set of independent local similarity measures, for each attribute, using equation below:

$$sim(f_i^N, f_i^R) = (f_i^N + f_i^R) \div 2$$
(1)

By using a weighted sum as incorporation function the similarity between two features (f_i^N, f_i^R) of case may be computed using the evaluation function, (Kolodner, 1993), which ranks the cases in the set according to the similarity to the target case based on weight features as follows:

Similarity (Case^N, Case^R) =
$$\frac{\sum_{i=1}^{n} w_i * sim(f_i^N, f_i^R)}{\sum_{i=1}^{n} w_i}$$
....(2)

w_i = different levels of importance attached to each feature. (Weight)

Nearest Neighbor retrieval will compute the similarity between stored cases and new input case based on weight feature. A typical evaluation function will be used to compute Nearest Neighbor matching [14] as shown in equation (2). The Inductive retrieval Algorithm will determine which feature does the best job in discriminating cases and generates a decision tree type structure to organize the cases in memory. Both algorithms will be combined for efficient performance. Since Nearest Neighbor is slow in retrieving when the case base is large, Inductive Indexing has a fast retrieval speed. The difference between Inductive approach and statistical approach is that in inductive learning approach, different assumptions and algorithms are used to generate knowledge structure. For example, [15], applied inductive learning methods to risk classification applications and found that inductive learning's classification performance was better than probit or logit analysis. They have concluded that this result can be attributed to the fact that inductive learning is free from parametric and structural assumptions that underlie statistical methods.

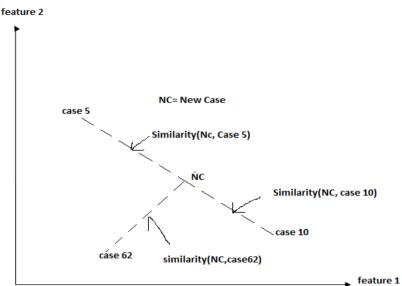


Figure 2, finding nearest neighbor of new case

The figure above displays a simple scheme for nearest-neighbor matching. In this 2-dimensional space, *case10* is selected as the nearest neighbor because *similarity* (*NC*, *case10*)> *similarity* (*NC*, *case5*) and *similarity* (*NC*, *case10*)> *similarity* (*NC*, *case62*).

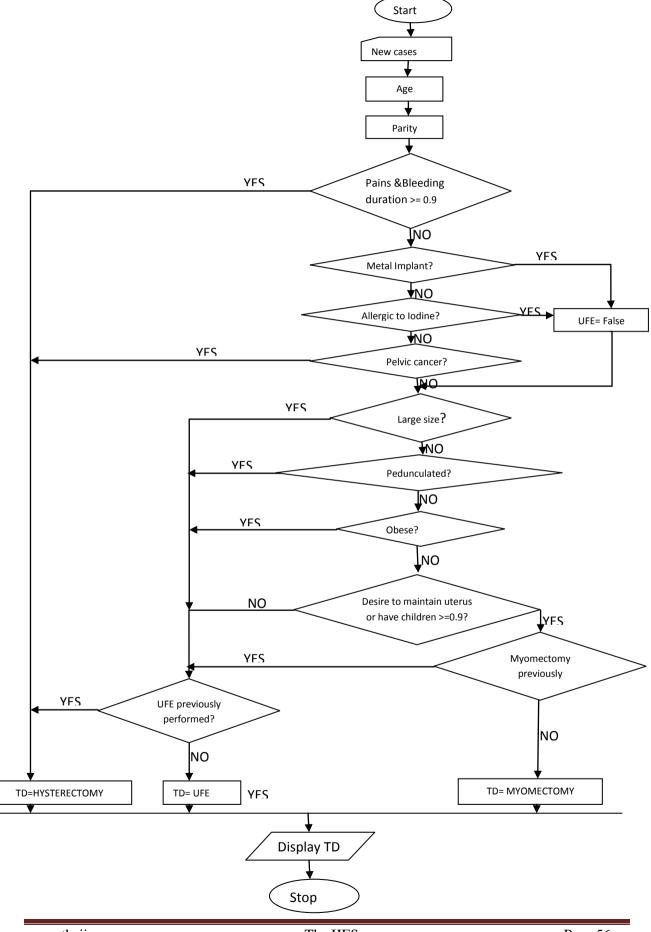
3.2 Case base Reasoning algorithm

Given a test case, a database, and a matching rule, the case-based reasoning algorithm is straightforward. From all cases in the database, those that match the test case are selected, and then the similarity fraction will be computed.

3.3 Matching Rule

The most important component of this system is the rule to decide whether a new case is similar to a case in the database. The following rule is considered:

- 1. Accept all cases.
- 2. The next logical matching rule is that the **Pain& heavy bleeding Duration** be matched.
- 3. Next, make a match for the patient's medical history: pelvic cancer, metal implant, allergic to iodine.
- 4. Next consider the size & location of the myoma.
- 5. Next consider if the patient is obese.
- 6. Then, consider patient's decision: desire to maintain uterus, desire to have children,
- 7. Next consider treatment formerly undertaken.
- 8. Then consider all findings.



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Figure 3: System Flowchart

3.4 System Algorithm

Step1: Compute the local similarity (that is, each feature of the new case and existing case features).

Similarity (Case^N, Case^R) =
$$\frac{\sum_{i=1}^{n} w_i * sim(f_i^N, f_i^R)}{\sum_{i=1}^{n} \sqrt{\sum_{i=1}^{n} w_i}}$$

 $w_{i=}$ Level of significance of a feature.

sim =Similarity function of features

 f_i^N and f_i^R are values for feature *i* in the input and retrieved cases respectively.

Step3: Sort the similarity values in ascending order

Step 4: The more similar case is retrieved.

By applying the local similarity measure, the similarity between features of various cases in the case base and the new case were obtained. The Global similarity measure is then applied to find the most similar existing case. The decision given to the case that appears with the highest value is also given to the new case.

IV. RESULTS AND DISCUSSION

A major attraction of this technique is its simplicity and intuitive clarity. The case based reasoning system estimates the answer to the question, "Of all cases that are similar to this one, which of them is the closest?" The mechanism is easy to understand: Find all of the previous cases that are similar, and then report the values of each, from where the case with highest value is selected. Fig. 4 shows the steps taken by the system to find the most similar case.

🖳 AutoMed: Fi	broid I	Patient	Data Ir	nput	. 7			-		-		🖳 AutoMed:	ibroid Patient Data Input	diameter.	
Question How old are you? (0 = <20; 1-20-25; 2-26-30; 3-31-35; 4-36-40; 5=41-45; 6=46-47; 7=48; 8=49; 9=50; 10=>50)		Question	What is your parity group?												
Select Answer	0	0.1 ©	0.2 ©	0.3 ©	0.4 ©	0.5 ©	0.6 ©	0.7 ©	0.8 ©	0.9 ©	1.0 ©	Select Answe	0 ©	1.0 •	
	P	revious							<u>N</u> ext				Previous	Next	

Figure 4, Fibroid patient Data input

Patient's condition is known by answering 12 different questions provided by the system. Finally a solution is provided based on the answers provided by the patient as seen in fig. 5 below.

×	ſ
Solution is UFE	
ОК	

Figure 5, Auto- med solution.

The global similarity value is finally made available, as shown in the fig. 5. From fig. 5 case 60 is the case with the highest value and the solution is UFE which the system suggested for the patient based on the answers she provided. The cases considered by the system as most similar are arranged in descending order. This makes it so easy to the user to understand.

•	AutoMed: Fibroid Case Study Matching	
	Global Similarity Values [case60, 0.601612903225806] [case53, 0.598387096774193] [case34, 0.593548387096774] [case38, 0.591935483870968] [case44, 0.588709677419355] [case12, 0.558695652173913] [case25, 0.54565217391304] [case23, 0.519565217391304] [case48, 0.493548387096774] [case48, 0.493548387096774] [case77, 0.298076923076923]	
	Save Case into Knowledge Base	

Figure 6, Fibroid case study matching.

One disadvantage of the case-based reasoning technique is the possibility that a new case will be presented that has no match in the database. Although this did not occur in the current database with the coarse matching criteria described previously, it is more likely to occur as more restrictive matching criteria are applied. This can be addressed by an adaptive matching criteria that will broaden the criteria for a case match, if too few matches are found, using a more strict criteria. Expansion of the database will also decrease the probability of such an occurrence.

V. CONCLUSION AND RECOMMENDATION

In this paper, useful demonstrations of CBR approach to decision making for Uterine Fibroid treatments were carried out. Inductive Indexing and Nearest Neighbor technique will both be applied in case retrieval phase. A user gains confidence in a system that provides correct results. However confidence is also improved in systems where the decision making process is transparent and deficiencies can be identified and resolved. The explanation of results should be a key design criterion in CBR systems. The system presented is user friendly and deficiencies can be easily identified.

The method in this paper could be extended to future research that employs other techniques. The processes described here could also be applicable to other types of medical decisions, preference-sensitive or otherwise, as well as other decision making domains.

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