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# Emerging medical informatics with case-based reasoning for aiding clinical decision in multi-agent system

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A B S T R A C T

This research aims to depict the methodological steps and tools about the combined operation of case-based reasoning (CBR) and multi-agent system (MAS) to expose the ontological application in the field of clinical decision support. The multi-agent architecture works for the consideration of the whole cycle of clinical decision-making adaptable to many medical aspects such as the diagnosis, prognosis, treatment, therapeutic monitoring of gastric cancer. In the multi-agent architecture, the ontological agent type employs the domain knowledge to ease the extraction of similar clinical cases and provide treatment suggestions to patients and physicians. Ontological agent is used for the extension of domain hierarchy and the interpretation of input requests. Case-based reasoning memorizes and restores experience data for solving similar problems, with the help of matching approach and defined interfaces of ontologies. A typical case is developed to illustrate the implementation of the knowledge acquisition and restitution of medical experts.





## 1. Introduction

Medicine is a science but also a discipline of action that often requires a decision. The complexity of decision-making, especially in medicine and public health, comes from the uncertainty, for example the uncertainty of knowledge, uncertainty about the facts and the uncertainty of the language used.

A multi-agent system (MAS) for decision-aiding support uses and combines databases, knowledge bases, ontologies, and various modes of reasoning according to the clinical approach. The clinical solutions emerge from the cooperation of agents specialized in clinical stages (diagnosis, prognosis, treatment, therapeutic monitoring) and knowledge bases developed with different models.

In the current multi-agent system [6,16], databases and computer records work together to ease decision making by improving access to relevant data through defined interfaces. We focus on the research of two types of problems with the help of case-based reasoning (CBR):

– Problems about classification or diagnosis. After investigating the uncertainty about the actual situation of the study object (patient, organ, population), it is necessary to separate the possible symptoms and diseases from the impossible ones to determine the effective measures;
– Problem about optimization. The purpose is to point out the most effective approach (e.g. therapeutic strategy) depending on goal and constraints such as the physical condition of the patient, drug contraindications, and drug secondary effect.

CBR is analogous to problem solving, which memorizes and restores experience data to solve similar cases. To make a clinical decision, first of all, we generate the clinical information like patient conditions, syndromes and medication characteristics by information retrieval. The knowledge elements such as class (concept), relation (verbs), instances (examples) and hierarchy are combined by defined interfaces and agents.

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Afterward, the information is mapped with the existing bases by CBR, to provide a list of clinical suggestions to physicians. The represented knowledge should be simple enough to be understood, but complex enough to contain most of the problems. In this case, the matching approach maps and extracts similar clinical cases, then provides visual suggestions. The ontology allows us to make use of medical knowledge base.

Several operation methods of system running are available: semi-active method is a system with automatic trigger responding to human intervention; active method is a system with automatic and autonomous trigger without interfering or supervising the decision maker. In our research, we use the passive method that requires explicit interaction from the user to describe the problem (e.g., the symptoms of disease, the patient's condition, etc.) and enquire the system. The presented system aims to provide treatment advice (e.g. diagnosis, prognosis, or medication usage of similar cases, etc.) to patients and physicians. Furthermore, all mentioned processes are monitored and formalized by the supervisor agent of multi-agents system to structure the problem and to assess the impact of alternatives.

## 2. Methods

### 2.1. Case-based reasoning

CBR is a qualitative and quantitative mixed model of experience storage and retrieval. This method is analogous to problem solving that compares new cases with previous indexed cases [1]. CBR involves semantic distances developed by different approaches: algorithms of structural similarity [10]; statistical learning as proposed by [20]; digital approaches from neural networks and fuzzy logic, etc. The researches about semantic distances tend to combine symbolic and numerical aspects [2,7,15].

Fig. 1 depicts an architecture describing the CBR process. It provides two main functions: storage of new cases in the database through case indexation module (right panel) and searching of indexed cases by computing the components similarities of new cases in case retrieval module (left panel).

In the case indexation module, cases are modeled as objects to build system knowledge. All cases are stored as object cases records.

The case retrieval module uses the database of indexed object cases and distance to evaluate the degree of partial structural similarity between stored cases and new cases being processed. When a new case occurs, most similar cases are subsequently searched, selected and adapted in the hope that the previous appropriate treatment will be suitable for the current case [3]. This searching function is carried out using matching approach detailed in Fig. 6.

When the case database is empty at the very beginning, we have to input or adopt existing knowledge base systems. For example, the online database «MedlinePlus dictionary of stomach cancer» can be downloaded and encapsulated in CBR for the reference of relevant catalogues (e.g. 419 studies for "Stomach Neoplasms" and 1667 studies for "Stomach cancer"). The cooperation features between CBR and MAS are exposed below.

### 2.2. Multi-agent system (MAS) for clinical decision support (CDS)

MAS instantiates the Supervisor Agent Type (SAT), the General Cognitive Agent Type (GCAT), the Knowledge Model Agent Type (KMAT) and the Domain Specific Agent Type (DSAT) types during two steps of specialization (Fig. 2). During the first specialization step, KMAT inherits the modules and features from GCAT, besides its own specific features. For example, a rule-based KMAT has access to an inference engine; the CBR of KMAT memorizes and restores experience to solve similar problems, etc. An epidemiological KMAT can reveal the incidence and prevalence of disease. The Supervisor Agent can be instantiated to guide the decision making process and to obtain the question answering in a reasonable time. An SAT is a specialized agent for clinical task diagnosis ($\Delta$), prognosis ($\Pi$), treatment ($\Theta$) and therapeutic monitoring ($S\Theta$), as well as a tool for knowledge retrieval with case-based reasoning (CBR) and ontology (Ontology).

The second specialization step produces DSAT and represents specific clinical stages $\Delta$, $\Pi$, $\Theta$, $S\Theta$ (e.g. the diagnosis of infectious disease, the prognosis depending on the overall condition of patient, and the treatment of bacterial infection with antibiotics). These agents use the knowledge models inherited from KMAT by producing rules, calculating distances between knowledge objects, using clinical case objects and statistics approaches. During each clinical stage, all involved agents transfer queries to specific knowledge databases for analysis and extraction. In this hybrid approach, the autonomy of DSAT is maintained: they have the ability to accept or decline a task according to their reflexive knowledge.

### 2.3. Medical decision process

The MAS proposed here is based on our previous work [6] and those of other authors [14,18]. MAS is modeled using Finite State Automata (FSA), which is a mathematical model of computation used to design computer programs and describe simple parts of natural languages grammars in our research. Our study defines a modular decision-making process by standardizing clinical decision protocol and regularizing medical task (Fig. 3).

In supervised MAS (Fig. 3), we describe the community of agents (e.g. SAT $\Delta$, $\Pi$, $\Theta$, $S\Theta$) that have been outlined in the last section. The transactional consistency for the planning and organization of decision-making tasks is carried out through FSA, which revolves around the decision process order of specific clinical stage such as diagnostic ($\Delta$), prognostic ($\Pi$), treatment ($\Theta$) and therapeutic monitoring ($S\Theta$) (not represented to be concise) (Fig. 3). The working memory can help to describe current situation and collect intermediate results.

SAT CBR [6] offers an approach for retrieval and storage of treated clinical cases, in order to build experience data corpus in MAS. SAT CBR successively stores and indexes clinical cases and knowledge under different directories ($\Delta$, $\Pi$, $\Theta$, $S\Theta$) by identifying keywords about problem of case (PB), environment (patient record) (E) and result (R).

With FSA, the supervisor monitors and triggers all necessary steps of clinical decision process, and ensures the dialogue between computer and final-user. It controls the management and execution of clinical tasks with predefined available agents. An agent is instructed to give up a task if the situation or operating environment is amended (e.g. the output of MAS is assumed by the user; the query has expired, etc.).

The models of knowledge (Fig. 2) are encapsulated in the agents detailed in Fig. 3. Each agent uses its reflexive knowledge to determine whether it should contribute in the task requested by the supervisor. The degree of specialization, the nature of the task, the knowledge available in the database, and the mode of reasoning are involved in this choice. If the agent accepts, the supervisor takes part into the on-going actions, and then the necessary agents become active. The answers are extracted and listed from MAS through matching approach by consulting the working memory and similar clinical cases, and by requesting information through the user interface.

MAS dialog user interface (Fig. 4) sums up results within an acceptable time. Overloading of supervisor interfaces and relatively low autonomy of agents are negative aspects. According to