# Enhanced Knowledge Management by Synchronizing Mind Maps and Fuzzy Cognitive Maps

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## 1 Introduction

People are constantly confronted with information. By acquiring, processing and understanding information, knowledge can be created, and managing this knowledge appropriately enables us to make better decisions. At first sight, this argumentation may seem logical, even self-evident, but it contains a hidden challenge: Conducting a conversation mostly involves natural language that consists of words and sentences (i.e., jointed words). It is not very difficult to form grammatically correct sentences. However, it is rather challenging to ensure different people understand them in the same way (cf. emergent semantics [3]). Everyone's background knowledge varies [21] and, even with today's advanced information and communication technologies, it is becoming increasingly difficult to manage all the information from different sources and to take the needs of all stakeholders into account. It is becoming increasingly essential to efficiently use existing knowledge to enhance everyone's living standards, and by using connectivism (i.e., connected learning and cognition theory), people can learn from one another [20] and thus benefit from others' experiences. One way to handle this challenge and also foster this potential is to develop and build cognitive systems that help users to cope with today's ever-increasing amount of information. Cognitive computing facilitates the communication between humans and computer systems, and problem solving and decision-making can be improved. Thus, knowledge management (i.e., the acquisition, aggregation and representation of knowledge [19]) can be enhanced. This paper is meant to elaborate on the framework proposed by D'Onofrio et al.

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[6]. It presents a more detailed insight into the idea of synchronizing mind maps (MMs) with fuzzy cognitive maps (FCMs). This framework should be able to gather and extract relevant information and thus support humans in collecting and evaluating them. This paper is an outline of a current work-in-progress, in which the authors pursue an approach relying on design science research [9]. It is a first step towards cognitive computing, according the law of parsimony. The goal is to develop cognitive systems that are able to store, connect and retrieve information like a human brain. According to Dewhurst and Conway [4], pictures are more likely to be recognized than words, which is why MMs are used to facilitate the acquisition and computation of words. Transforming MMs into FCMs enables machines to build efficient connections; therefore, retrieving the information is more efficient. The goal is a system that can think like a human and thus facilitate the communication between human and computers. Furthermore, cognitive systems should facilitate the exchange of experiences, so that people can share their knowledge (i.e., connectivism) [20]. These considerations are structured as follows: Sect. 2 presents the theoretical background; Sect. 3 outlines the proposed framework; Sect. 4 illustrates this framework with a use case concerning app development; and Sect. 5 concludes the paper.

## 2 Theoretical Background

This section explains the concepts of soft computing, creativity techniques and cognitive computing, all of which are required to understand the proposed approach.

### *2.1 Soft Computing*

Soft computing is a consortium of methodologies that play an important role in the conception, design, and utilization of cognitive systems. Dividing a case into granules (i.e., clusters) [30] is a way to analyze and solve problems. By introducing fuzzy set theory [27] into a crisp clustering process, fuzzy clustering (FCl) broadens traditional data clustering, as one element of a dataset can belong to multiple clusters. To structure and describe datasets, fuzzy logic [28] can be applied to identify similarities and differences among clusters for detecting knowledge [11] and patterns in the data [1]. FCMs can be used to represent knowledge and transfer it in a simple way, which consists of nodes (i.e., concepts) and edges (i.e., causal relationships between concepts). They model complex issues based on large amounts of data by reducing them to the essential causal dependencies. By applying fuzzy logic, FCMs can indicate how much the concepts influence one another by including edge weights within the interval [0,1] [15].

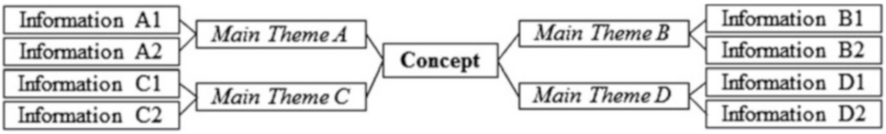


**Fig. 1** Principle of a MM

### *2.2 Creativity Techniques*

Creativity techniques help to collect information, look at problems from different perspectives and/or structure gathered information [8]. Based on the evaluation of Kaltenrieder et al. [12], MMs can be combined with FCMs. Their branches form a structure of interconnected nodes (similar to FCMs), allowing a structure that is hierarchical and network-oriented (see Fig. 1).

### *2.3 Cognitive Computing*

To cope with today's complex datasets [10], cognition and the principles of cognitive computing (i.e., connectivism [20], computational thinking [25] and intelligence amplification loop [13]) should be considered when constructing new systems. Cognitive computing aims to acquire, aggregate and represent data in an efficient way, so that people can manipulate and make inferences on the basis of the data [17].

## 3 The Conceptual Framework

This section addresses the proposed approach using the specified concepts above to give a better insight into the idea of the framework. Creativity techniques have been applied in various approaches in combination with FCMs (e.g., Eppler [7], Kontogianni et al. [14]), in scenario development (e.g., Stylios and Groumpos [23]) or for support in decision-making (e.g., Xirogiannies et al. [26]). Although this combination has previously been researched, there is still potential to elaborate it further. The contribution of this paper is its focus on using FCMs to process information that was explicitly acquired through MMs. As illustrated in Fig. 2 the framework consists of seven steps.

The following use case is based on this approach and explains the proposed framework in more detail.

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Code of Practice
Input: Information
Output: Aggregated FCM
1 Write relevant information on MMs
2 If enough information, continue with 3
  If not enough information, repete step 1
3 Apply FCl algorithm
4 Build FCMs
5 Translate linguistic variables into numeric values
6 Apply aggregation algorithm
7 Re-translate numeric values into linguistic variables
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**Fig. 2** Code of practice

## 4 Use Case: Smart City App

The fictitious example is a tourism company that wants to develop a smart city app to optimize their business. The specification process of the relevant features is complex, as the office seeks to involve all of its stakeholders. A way to streamline this process is to apply the proposed approach (see Sect. 3).

*Step 1* Stakeholders spend time brainstorming the project 'smart city app' and try to write keywords into MMs (e.g., needs, concerns, wishes). By applying fuzzy granulation, the information gathered through MMs is fractionalized into granules that support zooming-in-and-out functions (i.e., by focusing on a main theme, the underlying information appears). Several MMs can be created as a first step. An example of an MM is demonstrated in Fig. 3, showing main themes (e.g., sightseeing) and related information (e.g., guided tour).

*Step 2* When the brainstorming session is finished, the created MMs are submitted for conversion.

*Step 3* Information that belongs to a certain concept with a membership degree higher than a specified level (i.e., $\alpha$-cut [24]) is extracted using the FCl algorithm. For this framework, a method of FCl can be adapted from the thesis of Portmann [18]. So, in this use case, applying fuzzy granulation [30], following clusters are automatically built: accommodation, sightseeing, transport and gastronomy (see Fig. 4 adapted from Zadeh [31]).

*Step 4* The application of fuzzy granulation creates several main theme clusters (e.g., sightseeing) which are represented as FCMs. A possible example of extracted information from MMs to FCMs at a high level (i.e., without going into details) is depicted in Fig. 5. In this case, four main themes appear. The four axes in the square represent the fuzzy sets (i.e., main themes), whereas the points inside the square

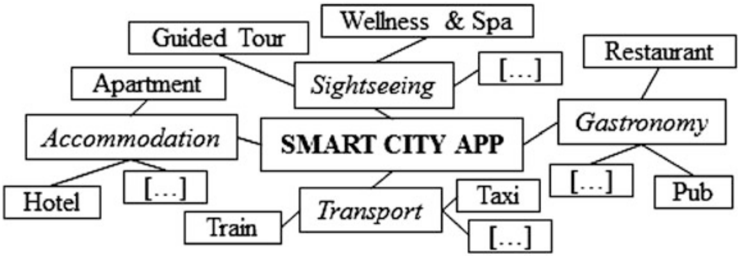


**Fig. 3** Example of a MM

Accommodation → AirBnB + Apartment + Bed & Breakfast + Hotel + ...
Sightseeing → Adventure Tour + Guided Tour + Historical Place + Wellness & Spa + ...
Transport → Bus + Taxi + Train + Subway + ...
Gastronomy → Pub + Restaurant + Take Away + Wine Cellar + ....

**Fig. 4** Clusters

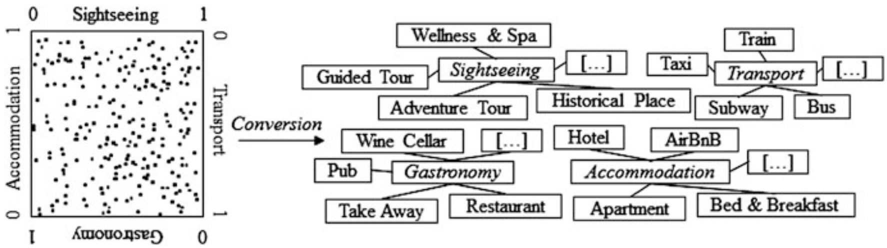


**Fig. 5** Conversion

incorporate the elements of data (i.e., related information) with their membership degree to these fuzzy sets [5].

Having assigned the data elements to the fuzzy sets, the information can be converted into FCMs. An initial mathematical formulation of this process can be found in the work of Stylios and Groumpos [23].

*Step 5* For the aggregation process, the linguistic variables of the created FCMs have to be translated into numeric values (e.g., with the help of computing with words (CWW) [29]), which, for now, is performed manually. Following the law of parsimony, one possibility is to use fuzzy if-then rules. Adapted from Zadeh [29], the following example can be obtained:

– If *Restaurant 1* is *mostly booked up* then *Service is good*. (1)

As mostly booked up and good are imprecise descriptions containing semantic values, fuzzy sets can be used to curtail the numeric values. In this example mostly booked up can mean that approximately 80% of the time the restaurant is booked

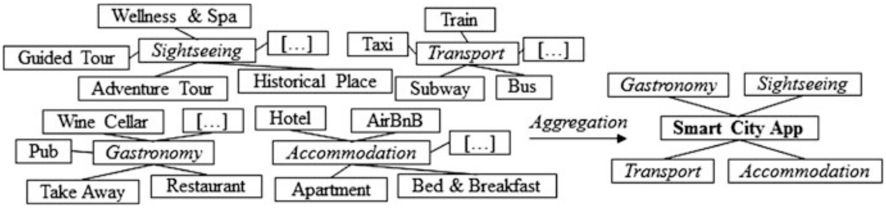


**Fig. 6** From FCMs to one FCM

up. The term good can mean that 9 of 10 customers are satisfied with the service. Thus,

– If *linguistic value* is *mostly booked up* then *numerical value is [0.8, 1]*. (2)
– If *linguistic value* is *good* then *numerical value is [0.9, 1]*. (3)

The numerical values are defined based on the membership function with an interval of [0,1] [28]. The more information that is available, the more connections can be built between this information, and the more accurate the fuzzy sets become; thus, better results can be obtained. Once these numerical values based on fuzzy sets have been obtained, the next step can be conducted.

*Step 6.* The various FCMs are aggregated into one large FCM (e.g., by taking the averages of the weights of the edges [19]) that represents all the relevant gathered information, as illustrated in Fig. 6. A mathematical formulation for this process can be found in the thesis of Stach [22]. In this case, one aggregated FCM (at a high level) with the name 'smart city app' is created.

*Step 7.* The numeric values have to be re-translated into linguistic variables so humans can understand the FCM.

To summarize, the aggregated FCM consists of different levels of granularity and thus allows the users (e.g., decision-makers) to zoom in and out [19, 21]. Thus, the proposed framework is in line with the needs of the decision-makers.

## 5 Conclusions and Outlook

This paper shows an exemplary adoption of the proposed approach by gathering information, splitting it into granules, converting it to (machine-readable) FCMs and finally aggregating it into one FCM. The contribution of this paper is its focus on using FCMs to process information that was explicitly acquired through MMs and to refine the concept proposed by D'Onofrio et al. [6]. The underlying vision of this framework consists of developing and building cognitive systems that allow semi-automated reasoning. The combination of MMs and FCMs can be highly beneficial in decision-making processes, as it helps to handle complex problems by taking advantage of human creativity. Using the proposed framework may help collective intelligence [16] to arise. This framework facilitates communications between humans and computer systems and, therefore, collaborations between people. Thus, knowledge management can be improved as well.

MMs encourage people to use their creativity and express their needs [2]. Furthermore, as granulation allows the compression of data [31], MMs are appropriate to reduce the complexity of an issue to essentials keywords. MMs are only useful to a certain extent, but their combination with FCMs results in an efficient approach to complex problem situations [12]. As FCMs depict causal relationships between concepts, they are able to represent knowledge for cognitive systems in a human-like way. Therefore, the proposed framework and the ongoing work-in-progress could provide an enhanced knowledge management system.

The authors worked with elaborated mathematical formulations of other researchers to ensure a basis for the proposed framework. These researchers have been referred in this paper. One of the next steps consists of refining these formulations in more detail and identifying algorithms that fit the presented approach.

As soon as the mathematical foundations are elaborated, the conceptual approach will be tested and evaluated. In addition, the link between MMs and FCMs should be measured. However, at this phase of the work-in-progress, it is not yet possible to make such evaluations. Nevertheless, the evaluation is an essential step in this development; thus, if this approach obtains reasonable outputs on real datasets, the authors will evaluate it. If the results are positive, further evaluations will be performed to find out if these outputs are better than other, simpler methods.

Furthermore, to make the aggregation of various FCMs possible, an automatic transformation from linguistic information into numeric information (and vice versa) must be developed. Concerning this process, an implementation of CWW (e.g., fuzzy if-then rules) is interesting. As words can be mathematically translated using fuzzy sets, CWW's perception of words as granules makes computation with information in natural language possible [29].

Even if MMs can gather as much information as possible from different stake-holders, this technique simply focuses on words. Therefore, other creative techniques (e.g., scenarios and user stories) are required to build meaningful sentences, as the semantic part of a sentence is more difficult to create than the syntactic part.

Furthermore, the proposed framework will be evaluated by different stakeholders to gain qualitative inputs and feedback.

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