Computational Creativity: The Design of a Creative Computer Program

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Abstract—**Computer and cognitive scientists are making serious attempts via developing algorithms which aim to simulate some aspects of human's cognitive behavior.**
In this context, it is not surprising that research efforts are directed towards studying human's creativity in an attempt to understand how humans produce creative content, and in what sense does it differ from cognitive content.
The idea we are proposing in this research is that we may to a certain level, though humble, emulate some aspects of human creativity. We propose a method which involves designing a program that generates content that could be considered creative. It is important to note that we are not making any claim about matching human creativity level which we believe is limitless and cannot be measured. We shall apply our proposed program on a field that is considered as one of the creative fields in human life and that is based on the idea of combinatorial creativity. The field is culinary arts. The program has been tested to generate creative culinary content using the culinary knowledge of certain Arabic countries and modeling their culinary practice into several steps inspired by the pattern of their process of combining several ingredients.
The results were satisfying where only 2 out of 255 were considered as unacceptable results. The program showed its ability in generating creative content in the field of culinary arts. We aim to expand our experiments and to generalize this program to suit several artistic domains.

Keywords—Artificial Intelligence; Machine Learning; Computational Creativity Monte Carlo; Culinary Arts; Food Pairing; Flavor Network.

I. INTRODUCTION

Many people think that creativity is magical. However, researchers believe that it is actually something that could be studied, investigated and modeled [14]. Gustavi and Jandel [23] defined creativity as "*The ability to generate novel and valuable ideas, concepts and artifacts where novelty and value are adjudicated by some receiving human or group of humans"*.
Boden (1992)[28] listed three types of creativity:
A. Exploratory creativity: exploring a space of novel solutions.
B. Combinatorial creativity: combining elements of previous solutions and create new solutions.
C. Transformational creativity: transform existing solutions in a novel way that might suit another similar problem, or solve a problem with inspiration from other existing solutions.

Artificial Intelligence (AI) techniques can help in simulating the creative behavior of humans. We could work towards achieving programmatic representation of creativity which can be used by humans to trigger and/or enhance their ability of innovation and creativity in artistic domains such as music, poetry, comedy, etc. [14] [15] and non-artistic fields such as planning and decision making [23]. Creativity can be described as an evolutionary process that embraces novelty and values [23] where the values differ from one domain to another.

Computational creativity is considered as a sub-field from AI field [15]. And it could be applied in so many ways; the main idea of computational creativity applications is building a procedure to produce novel content (generating new material) using current knowledge and stored artifacts. The building of this intelligent process depends on its nature; it must follow the same pattern that is used in a human's life to produce new material in any specific area.

This paper aims to design a program that follows the concept of combinatorial creativity, to automate the process of combining a set of elements from various groups in a stochastic approach that follows the unexpectedness in human's creativity. Such approach could be applied in various domains for example combining a set of rhyming words to help write a poem is a creative process performed by poets, also combining a set of compatible food elements to be put in a recipe is also a creative process done by a cook.

In this paper, we chose to simulate the novelty in the culinary art field and find out to what extent the culinary practice of humans could be simulated. After our previous work on analyzing and studying the pattern of culinary evolution in the chosen Arabic countries [22], we continue this work to take advantage of the investigation that was performed on the

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cuisines of (Jordan, Syria, Lebanon, and Palestine) and the previously extracted information to build a knowledge base that feeds such a creative program. This will lead us to an approach that suits the culinary practice of Arab people in the chosen countries. Our approach for building a creative culinary product contains three major steps: (1) designing the product, (2) building the product, and (3) assessing the product.

First, and following the combinatorial creativity concept, the components of the product are selected from multiple categories, whereas the number of categories varies according to the problem domain. Using a controlled stochastic method to design the product with respect to existing solutions that were already created by humans by hiring their creativity. Then, using a graph-based algorithm, product elements are chosen from network-modeled groups where each category is represented as a network of connected elements with weighted links that hold a compatibility measure between elements. Finally, the product is evaluated to test its acceptability and novelty.

The paper is organized as follows: in Section II we discuss some related work in the area of culinary arts and computational creativity. Section III contains the data source and format. Section IV discusses our approach in details. Section V contains results and analysis, and Section VI is dedicated to conclusions and future work.

II. Related Work

Computational creativity is a multi-discipline area that could be found in various domains [23].

Many people have implemented several solutions that automate the creative behavior of humans in many fields, such as decision making [24], marketing [25], and natural language generation such as (poetry, comedy, and short stories) [27].

IBM is one of the leading groups in research in the area of computational creativity, after building the supercomputer, Dr. Watson. They have designed a framework that produces creative content and added an assessment step which hired the cognitive procedures to assess the produced content and test its creativity [2]. Then, they used this framework to produce novel culinary recipes with the use of evolutionary algorithms.

When talking about producing novel recipes, we talk about programs that learn to combine ingredients and not just retrieve already existing recipes written by humans.

There are many studies that took a step towards producing new content and was focused on culinary art field only by adding some new modifications on existing recipes based on many features such as: available ingredients [3], nutritional intake [4][5], user's ratings [6][7], finding similar recipes with overlapping ingredients [8], grocery shopping recommendation [9] [10], and meal planning [11].

Another branch is producing recipes with substitutions for some ingredients or some modifications (inspired by the user's ratings and views over the recipes) to recommend new versions of recipes. [12]

Some people relied on the semantic analysis in such field such as Cooking up Referring Expressions [13] which is a computer program that uses EPICURE which is a natural language generation system whose principal concern is the generation of referring expressions which pick out complex entities in connected discourse and produces natural language descriptions of cookery recipes.

This research focuses on producing novel recipes by building a program that produces novel content and works in a way similar to producing creativity in human's minds.

In the field of computational creativity, Colton and Wiggins [15] have talked about computational creativity, the way it can be applied, and the areas it can be applied in. Few people examined computational creativity in culinary art such as Cromwell and Ramanujan [18] who have used automated salad recipe generator and tested the results with comparison to human-made recipes. On the other hand, Varshney and Pinel [19] have also examined generating recipes by building a generative program to follow the generative nature of human creative ideas to create several recipe ideas, they have also considered the flavor pairing hypothesis in their quality measurements for results, but with a different approach than ours.

We want to take a deeper step in this field and enhance the studies made in the culinary art field by considering the Arab countries for our study, and following a different path with designing, building, and evaluating creative culinary content. We also hope that the efficiency of this creative method could be proved to design creative content in many areas not just the area of culinary arts.

III. Data

Every human has previous experience and known information that form his state of mind at any stage in life, ideas and thoughts of humans usually combine all of his previous experience and previously known information saved in the semantic network of his brain, but with a unique addition added to any decision or solution. Therefore, in order to model this process; the first step is to model the knowledge base of a certain field in a way that a human mind could represent, for example; modeling information with crossing links to build a network that looks like the semantic network in human's brains. The elements that form the product are categorized according to the domain nature, and a weighted graph of nodes is represented for each category. The weight represents the compatibility of a pair of elements that has a link which connects them. Thus, a measurement of compatibility is needed to set those links, and this measurement could be set by experts in the field.

In our case, the groups are divided according to main food groups, and the filled data is food ingredients. Finally, the connections between those ingredients are set with respect to the flavor pairing hypothesis [21] that calculates the compatibility of ingredients according to aromatic chemical features of any ingredient. So our analysis was done on the recipes and ingredients level.

The culinary recipes in any region describe the culinary practice of people within this region and hold the real way of combining ingredients by those people. The recipes provided by the

famous Arabic cooking application, Atbaki [16] were chosen in this study.
Atbaki website contains 712 recipes provided under the categories of four countries (Jordan, Syria, Lebanon, and Palestine). We made sure that the collected recipes contain the traditional recipes known from those countries.
The data cleaning process consisted of:

- Removing the portions: replacing “½ cup of flour” with “flour”.
- Renaming some ingredients with respect to names in the famous flavor network [21]: replacing “flour” with “whole_grain_wheat_flour”.
- Translating the recipes to English because they were written in Arabic.
- Every composite ingredient was entered as a set of raw ingredients: mixed spices for example; was entered as the 7 raw spices that form this combination.

Recipes were collected and entered into a database, some statistical data were calculated for the needs of our study, like frequencies of ingredients, categories usage, categories priorities, and some other numbers needed for building the rules that control the process of shaping the product.
After that, ingredients were divided into graph networks according to their food groups, we considered the main food groups: Vegetables, Spices/Herbs, Plants, Fruit, etc. Since the flavor compound hypothesis [22] has been confirmed for this area, it is suitable to represent the compatibility of ingredients at this study.

IV. Approach

This study aims at producing novel content in the field of culinary art using a computational creativity algorithm. We consider the culinary practice of Arabs living in Syria, Jordan, Palestine, and Lebanon; those countries have similar culinary practices due to the geographical closure. After studying and analyzing their pattern of ingredients combination and their style of cooking new dishes, our study showed that it’s an evolutionary process depending on some old recipes people know from their ancestors with modifications added by each generation or individuals to suit their taste or experience. Those changes could be random or inspired from other recipes.
One of the keys to a good recipe is choosing a good combination of ingredients. Ingredients combinations usually differ from one nationality to another. So, we ask the following research questions: can we build a method that simulates the culinary practice of people at this area to combine ingredients according to their taste but with acceptable additions?
We applied this idea in an approach that contains 3 main steps: (1) defining the shape of the product, (2) forming the product, and (3) assessing the product.

Step 1: Defining the shape of the product
The expected result should be highly similar to what humans know and experience, but with the element of surprise to give it a creativity print. So as a first step, the expected shape of the result should be determined so that it could guide the process of building the final product.

Due to the stochastic nature of creatively created products in general, we chose one of the stochastic based machine learning algorithms which are Monte Carlo Algorithm that is used for optimization and prediction, classified in machine learning under reinforcement learning algorithms [17]. Stochastic methods are optimization methods that have unpredictable results because of random variables or random constraints or random objects, which simulates the uncertainties in the world of creativity in general and which will add the magic that describes the novelty of creating a new product. Spall [20] explained stochastic methods as *"Methods for stochastic optimization provide a means of coping with inherent system noise and coping with models or systems that are highly nonlinear, high dimensional, or otherwise inappropriate for classical deterministic methods of optimization. Stochastic optimization algorithms have broad application to problems in statistics (e.g., the design of experiments and response surface modeling), science, engineering, and business”.*
In contrast, unlike stochastic methods, deterministic optimization methods assume that perfect information is available and that this information is used to determine the search direction in a deterministic manner at every step of the algorithm. In many practical problems, such information is not available, and in our case, cooking is one of those practical problems that doesn't have perfect or accurately measured information in order to automate the process of recipe creation. Add to that, no one could describe human creativity as a deterministic process. Usually, in optimization and search methods, results aren't expected, unlike the deterministic methods; it depends on the nature of the problem. Figure 1 shows how Monte Carlo is classified in stochastic methods.

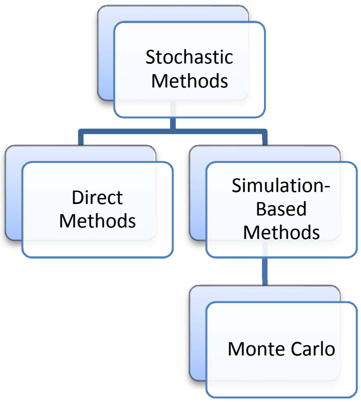

Figure 1: Stochastic Methods

There are many other stochastic optimization methods such as evolutionary algorithms which are population-based methods that use adaptation and evolution to keep on generating new solutions until finding the global optimal solution to achieve a certain goal, this method was considered by IBM at chef Watson [2].
The randomness calculated in Monte Carlo method could take several shapes such as uniform-random (which is having equivalent probabilities for elements being picked), and empirical distribution (which is controlling the probability of each element to be picked to increase the possibility of a common element to be picked). The empirical distribution

model allows us to control the shape of appearing result based on the culinary thinking of people, by controlling the probability distribution of random variables to control the appearance of certain ingredients according to their usage in the culinary practice of those countries over the years, of course, such information was extracted from the analysis we performed over the existing cooking recipes.

The empirical distribution model is used in our method to generate random numbers with different probabilities for each choice in order to determine the number of ingredients to be taken from every food group.

This is mainly how cooking in real life is; the number of ingredients is randomly picked by the cook according to his/her experience with a variety of recipes and according to previously chosen elements, and the number limits of choosing a set of ingredients from the same food group is set by the culinary knowledge of people in a certain area, stored in their existing food recipes.

Step 2: Forming the product

At this stage, the actual product is built, where it is formed with respect to the defined shape of the product. In our case, this step is about generating a set of ingredients to form the final recipe. In the domain of culinary arts, choosing ingredients sets or pairing ingredients together is the key step towards building recipes, The system knowledge is designed as graph networks with ingredients being the nodes and the links represent the chemical compatibility of each pair of ingredients, and this compatibility is set based on the famous flavor network hypothesis introduced by Ahn and Ahnert [13], who designed flavor network that captures the flavor chemical compounds shared by culinary ingredients and was built on food pairing hypothesis. Figure 2 shows the backbone of this flavor network. Since that our previous analysis has proved this hypothesis to be positive for our region [22], we found it suitable to use it as a measurement of compatibility of food ingredients.

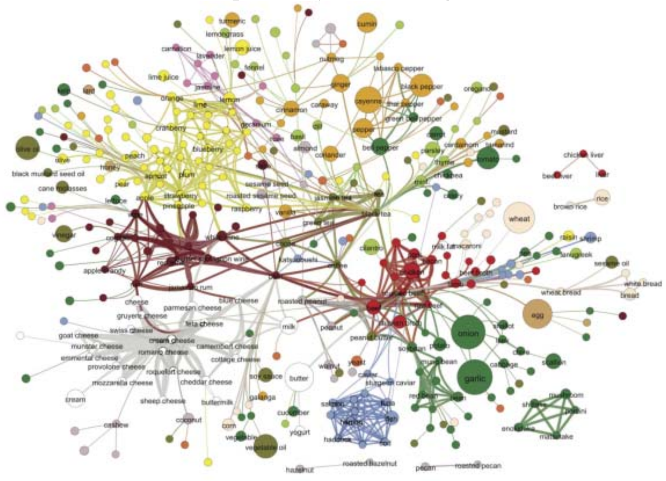

Figure 2: The backbone of the flavor network

Since that there are probabilistic constraints set over every food group, we categorize the ingredients in different groups, and each group is represented by an individual graph.

When combining ingredients, a high level of compatibility must be achieved, so, the set of chosen elements must be picked carefully to get satisfying results. Therefore, we built a modified Maximum Spanning Tree algorithm [26] that satisfies this goal; by picking elements that have high compatibility by making some local decisions on what's the best current element to take according to the previous element it chose and stops when it reaches the number of ingredients determined for this category. Each time the program runs, the algorithm starts from a random point on the network. Then it moves to another category and stops when the total number of ingredients for this recipe is achieved.

Novel ingredient combinations could be generated with an element of surprise using the randomness provided by Monte Carlo method, also, with the element of familiarity to get satisfying results.

Step 3: Assessing the product

At this step, the created product is assessed. The evaluation of a product depends on the nature of its type because computational creativity is hired to get something that "makes sense".

In general, in the artistic fields, there is no definition of what an optimal solution can be, it's very subjective and hard to measure, but its acceptability could be measured using existing data that sums up the taste of certain people. Since that our area confirmed the flavor pairing hypothesis it was used in this study to measure the fitness of each produced recipe.

A general strategy depending on whether the dish could be acceptable in this region or not, is suitable to evaluate the output of the program. This strategy is based on the pattern of usage for ingredients in existing recipes which plays a big role in the acceptance of this ingredient in the region's dishes. And the usage of these ingredients in a certain region is affected by their flavor perception which is formed by culture, climate, geography, and genetics [29].

A fitness function is built to calculates the average of compatibility of ingredients (average of the edges weights between all ingredients in the generated combination). This function ran on all the analyzed existing recipes and gave us an indication about minimum acceptable fitness which the fitness values shouldn't go below. This function provides a formal measure to tell if a generated recipe is acceptable or not, and in order to justify the way we built this process, then, system's evaluation of a couple of results were compared with a professional chef's evaluation. The chef's evaluation approved the approach followed in this study, also approved the used evaluation criteria which imply its validity of assessing creatively produced products.

V. RESULTS AND EVALUATION

Creative programs are designed to imitate the creativity of humans [14] and aid them with producing creativity. Our program followed that aspect by combining ingredients but leaving the recipes formulation (portions, and methods) to the users to enhance their culinary talents of the application of recipes, so the same ingredient combination could form more than one recipe. The ingredients combinations that were produced by our program came out to be interestingly new and somehow familiar.

The evaluation of our results consisted of 2 parts:

(1) Evaluation using a fitness function

The fitness function was designed with respect to flavor compound hypothesis because as previously mentioned it was confirmed for the cuisines of Jordan, Palestine, Lebanon, and Syria. So, the fitness value of a combination will be represented as the average flavor compounds value of these combinations. There is no definition of what a perfect recipe is, because of the subjectivity nature of such a field, so in order to tell whether a combination could be acceptable; the fitness of the combination is tested to check whether it's above a threshold which is the minimum fitness found in analyzed existing recipes from the chosen region, so that the results won't be very unfamiliar to people. Table 1 shows an evaluation of a sample of generated recipes.

Table 1: Sample of generated recipes

Result	**Fitness**	**Evaluation**
Rosemary, freekeh, bulgur, flour, ketchup	0.062	Bad recipe. (below the minimum fitness 0.5)
Thyme, onion, garlic, lemon, jalapeno, coriander, carrot, anise, black pepper, beef, long-grain-rice, flour, short-grain-rice, halloumi-cheese.	2.209	Good recipe. (above the minimum fitness 0.5)
Lemon, onion, garlic, parsley, tomato, coriander, nutmeg, black pepper, cinnamon, cardamom, clove, cumin, dry-coriander, turmeric, paprika, feta-cheese, egg, yogurt.	3.801	Good recipe. (above the minimum fitness 0.5)

(2) Evaluation by professional chefs

Since that the culinary practice field is very subjective and the evaluation of products in this field depends on the user's personal favorite flavors and experience in the culinary field, we chose to ask for professional chef's evaluation to give us a non-subjective opinion, also to get feedback on our product evaluation process performed by the system that generates the creative content.

We started by asking chef Khalid Abu Eid (the head of The Jordanian Chefs Association and an instructor at The Royal Academy for Culinary Arts) of his opinion about our method, he said " It's a creative method that would enhance chefs creativity when combining ingredients, it goes to a depth that not all chefs might consider when combining ingredients, we might even use it in The Royal Academy of Culinary Arts", we also asked chef Khalid to evaluate a set of generated recipes to validate the evaluation method in this study, his evaluation approved the evaluation method in this study which is about calculating the fitness of each produced recipe. Table 2 shows a sample of generated recipes with fitness level and the chef's evaluation.

Table 2: Comparison of fitness measurements and chef's evaluation.

Ingredients combination	Fitness value	Chef Khalid's evaluation.
Tomato, Onion, Garlic, Marjoram, Beef, Flour, Bean, Chickpea, Sugar, Pomegranate, Bran, Cashew-nut.	1.486	Those ingredients can be cooked as a recipe; I don't think pomegranate is 100% suitable for this recipe.
Ginger, Onion, Garlic, Tomato, Jalapeno, Parsley, Chicken, Corn, Ketchup, Margarine, Sesame-oil, Butter.	2.035	Those ingredients can be cooked as a recipe.
Rosemary, Freekeh, Burgul, Flour, Ketchup.	0.0622 (unacceptable fitness)	Those ingredients cannot be cooked as a recipe.

In general, most of the generated recipes were above the minimum fitness level which means that they are acceptable recipes; only 2 out of 255 generated recipes were below the minimum fitness, this indicates that the program we designed produces compatible combinations of elements that are widely accepted by humans.

VI. Conclusions and Future Work

Human inspired methods are used in the field of computer science to provide options for solving many problems. Human creativity is very interesting and inspiring that many research attempts were made to emulate human creativity to either find new solutions for certain problems or build creative based programs that aid humans. In this work, we proposed a method that combines food ingredients to form novel recipes inspired by the culinary practice of some Arabic countries. For future work, the method could be extended to add another region with different cooking habits; we might be able to produce hybrid recipes, also this method might be used in a different domain that is based on the idea of combining element. We're not making huge assumptions, but we have planted a seed that could grow in the field of computational creativity, by designing a program that could work as a creativity generator in many fields.

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