From Smell Phenomenon to Smell Agent Optimization (SAO): A Feasibility Study

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Abstract—*This paper presents a feasibility study, towards the development of a novel computational intelligent algorithm using the phenomenon of smell. According to literature, de-pending on the olfactory size of an organism (agent) and psychological condition, every living organism has a specific ability to perceive smell molecules (olfaction) and intuitively trail these molecules until its source is identified. Using this idea, this paper presents the possibility of developing a novel computational Intelligent algorithm called the Smell Agent Optimization (SAO). The idea of the SAO will be based on the evaporation of smell molecules in the form of gas and the perception capability of a smell agent. The mathematical model of the SAO will consist of three modes (Sniffing mode, Tailing mode and Random mode). When developed, the algorithm is expected to compete favorably with already established algorithm like ABC, GA, PSO etc.*

Keyword—Smell Agent Optimization (SAO); Smell Molecules; Sniffing Mode; Trailing Mode; Random Mode.

1 INTRODUCTION

Attempt to adopt an acceptable definition of intelligence still elicit debates among various disciplines. Dictionaries [1], [2] have defined intelligence as the power of under-standing, comprehending and profiting from experience, the power to interpret and having the capability for thought and reason especially to a high degree. The mechanisms of this intelligence, which are exhibited by all living sys-tems, share similarities in terms of complexity, organization, and adaptability as a whole. Over the years, experts have understandably sought for means of codifying these intel-ligence systems into algorithms dedicated to solving some complex problems in engineering and related disciplines. This triggered the development of a new field of study called computational intelligence (CI) which was popularized by James C. Bezdek about 23 years ago [3]. Perhaps, the first appearance of CI was way back in 1983 when the term international Journal of Computational Intelligence (IJCI) was reported to be the title of the Canadian journal by its editors and founders Gordon McCalla and Nick Cercone [5], [6] stated that computational intelligence consists of any science supported approaches and technologies for analyzing, creating, and developing intelligent systems. Intelligent in this case refers to the utilization of engineering techniques that have, to one extent or another, been borne out of human reasoning, adaptation or learning, biological cognitive structures or principles of evolution, natural phys-ical or chemical processes. Many experts have also referred to the term computational intelligence (CI) as the ability of a computer system to learn precisely a specific task, from a given set of data and/or empirical observation [7]. The IEEE Neural Network Council and the IEEE World Congress on Computational Intelligence formalized this term in the sum-mer of 1994 in Orlando, Florida [8]. Till, date, researchers have not come to a conclusive agreement as to a precise definition of computational intelligence [9]. This is because it is difficult to start with anything precise; the precision has to be achieved through a certain process. But, strictly speak-ing, computational intelligence is a set of nature-inspired computational models and approaches capable of addressing real-world problems to which traditional or mathematical model may fail due to any or all of the following reasons:

I. The problem or process may be too complex for mathematical reasoning.
II. The problem or process may be dynamic and stochastic in nature.
III. The solution space of the problem may be too large for mathematical computation.
IV. The problem or process may contain some uncer-tainties.

All these characteristics are exhibited by most real life (non-linear) science, economic, social and engineering problems. These non-linear type problems require several assumptions in order to transform them to their near-linear equivalents for easy computation. However, the outputs of such linear computations usually do not depict entirely the real-life situations. Therefore, agent-based computational intelligent techniques are capable of providing superb and promising alternatives in this scenario. In the past decades, researchers have developed various agent-based biological and nature-inspired CI algorithms for solving various optimization problems. The foraging behaviors of ant systems were cod-ified into an algorithm in [10]. Algorithms based on the intelligent behaviour of fish [11], bacterial foraging [12], Firefly [13], swarm particles [14], bee [15], Brownian mo-tion of gas [16], fruit fly [17], shark smell [18] etc. have also been developed. The performance of all these algorithms on suitable problems such as in [19], [20], [21], [22], [23] has demonstrated their effectiveness in solving real word problems. It is, however, important to note that, there is no known single nature-inspired optimization method available for solving all optimization problems (which is called the no free lunch theorem). This is because every real word problem can directly or indirectly be formulated as a so-lution using a particular algorithm that mimics a nature or bio-inspired phenomena.

For example, the pheromone trail and pattern movement of ant system can be said to mimic the lane and edge detection problem in transportation and image processing respectively. Similarly, the path planning and trajectory problem of a robot can be linked to an agent seeking to identify the molecular movement of an object (smell) which evaporates and travels into the olfactory organ (nose) of an agent, where they activate special cells that send a message to the brain for adequate judgment. Thus, this paper seeks to study the feasibility of codifying the intuitive movement of an agent towards smell (odorant) molecule as the agent seeks to identify the source of that smell or odorant. One of the five senses through which the world is perceived is the sense of smell (olfactory). Through the sense of smell, humans and other animals can perceive a large number and varieties of chemicals in the external world [24]. In fact, with a good sense of smell, humans and other agents (especially dogs) can perceive the molecular concentration of smell and intuitively trace or follow this concentration in order to identify its source.

This is possible because the nose has a mechanism that can recognize sensory information within its surroundings and transmit the information to the brain, where it is processed to simulate internal representation of the external world [25]. These representations help the smell agent to determine the optimized path which constitutes the search or solution space. In this case, the object which radiates the odor molecule is the solution that resides in the search space. Based on this, this paper hopes to provide detail information which enables the development of an optimization algorithm using the path trailing ability of smell agents for solving various degrees of combinatorial optimization problems. In virtually all optimization problems, the complexity and structure of the problems increase as the dimension of the problem increase. In such situations, an exhaustive search is not feasible. Thus, a technique capable of operating in a domain of such optimization problems in which a set of possible solution is discrete or can be reduced to discrete with a common goal of finding the best solution is termed combinatorial optimization. Combinatorial optimization is an indication of optimization problems with an extremely large (combinatorial) increase in the number of possible solutions as the problem size increases.

2 MATERIALS AND METHODS

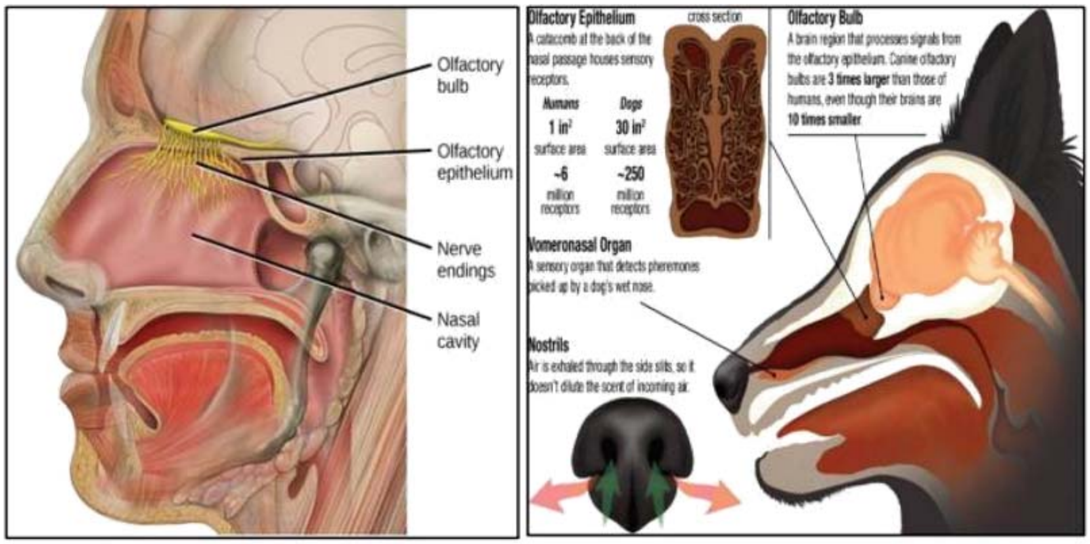
In this section, the fundamental theory which support the modeling of the smell agent optimization are provided. When necessary, readers are also referred to relevant litera-tures for further study.

2.1 Phenomenon of Smell (Olfaction)

Full Smell is defined as the ability to perceive the odour or scent of something through the nose by means of the olfactory nerves [2]. This are usually, made of chemical compound of different molecules evaporating from a source with a molecular weight of less than 300 Dalton [26]. Detection and discrimination of this chemicals in the en-vironment are critical for the survival of most organisms. Virtually, all organisms ranging from the simplest unicellular form to the most advanced multicellular creature possess the capability to detect chemicals in their surroundings through a process called chemosensation [27]. Chemosensation relies on the olfactory systems which contain a large number of chemoreceptors used by organisms to locate food, mates and avoiding danger. These chemoreceptors are generally classified into odorant receptors and pheromone receptors which principally detect general odours and pheromones respectively [28]. The chemical compounds which are odour molecules travels into the nasal cavity, where they are detected by the olfactory receptors. At this point, the ol-factory receptor neuron fires and transmits an impulse into the olfactory bulb at the top of the nasal passage.

This connects to the olfactory centre in the cerebral cortex for odour perception and recognition and to the limbic system which controls the expression of emotion and instinctive behaviors. Researchers have estimated about five to six million olfactory receptors in man, each having a specific sensation for a particular ligand (ligand in this case refers to a specific sensation for a particular smell molecule). This enables man to be able to detect over one trillion differ-ent odours [30]. It is however believed that each odorant molecules triggers several olfactory receptors which create a unique combination of neural impulses that is interpreted as a single odour scent. An interesting thing to note is that, despite the olfaction capability of man, agents such as dogs, rabbits etc. have a stronger olfaction capacity. For example, dogs have been said to have over 220 million olfactory receptors which account for their dazzling sense of smell [24]. As an illustration, Fig.1(a) and Fig.1(b) show the biological structures of the olfactory systems in man and dog respectively [24], [31]. The chemosensation process of the agents shown in Fig. 1, and in fact every which has the faculty of olfaction, follows the same process highlighted as follows:

I. Evaporation
II. Stimulation
III. Transduction
IV. Transmission
V. Interpretation



(a): Man (b): Dog

Figure 1. Olfactory Syste

At the evaporation stage, the molecular vibration of an object which has smell capabilities evaporates chemical compound which travels into an agent nasal cavity at a molecular weight of less than 300 Dalton. At the stimulation stage, the chemical compound interferes with the nerve endings of the olfactory epithelium which generates a specific stimulating energy for the chemical compound. An electrochemical (chemosensation) nerve impulse is therefore produced by the olfactory receptors through transduction. The electrochemical impulse is then transmitted through action potential along different pathways into the brain. The brain then interprets and creates perception from the electrochemical event produced by stimulation. This action of the brain is what an agent perceives as the smell.

From the perspective of chemistry, smell (odor or fragrance) is generated by one or more chemical compounds generally at a very low concentration that humans or agents can perceive through olfaction [30]. Smell and taste are the chemical sense indicators of every agent as they allow an agent to be aware of the presence of chemical substances in their environments. The ability to detect these substances is predicated on the chemical nature of their molecules [28], [32] and the vibration of this molecules. Chemists have over the years identified that atoms in a molecule vibrate at a particular frequency depending on their overall molecular structure. In fact, a single change of atom in the molecular structure can make the smell molecules to vibrate at a much higher frequency resulting in variation of smell perception [29]. This accounts for why smell molecules of a very close structure and mass differs in terms of perception. For example, the fragrance (smell) of wintergreen which is used predominantly in mints, candies, mouthwashes, and toothpaste has the same molecular structure with vanilla fragrance (smell) which is used to make ice cream and chocolate. The molecular formula of the wintergreen is $C_8H_8O_3$ and the molecular structure is shown in Fig.2 while the molecular formula of vanilla is also $C_8H_8O_3$ and its molecular structure is as shown in Fig.3 respectively [32].

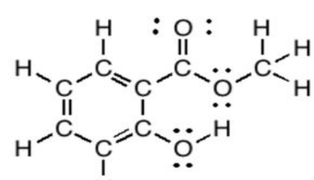


Figure 2. Molecular Structure of Methyl Salicylate (Wintergreen) [34]

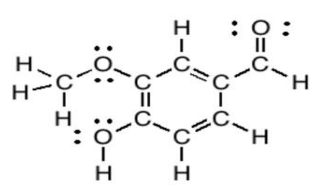


Figure 3. Molecular Structure of Vanillin (Vanilla) [34]

From, Fig.2 and Fig.3, it can be observed that, though both wintergreen and vanilla have the same molecular for-mula and structure, the variation in their fragrance are attributed to the positioning and bonding of the functional group which in this case is an ester and aldehyde respec-tively. Detail characteristics of this functional group are beyond the scope of this paper. However, readers who are interested in this information can refer to [33], [34]. For a smell molecule to be perceptible by an agent, the chemical composition of the smell has to be lipophilic, small (with a molecular weight of less than 300 Da) and volatile [34].

Of interest in this research is the molecular mass (weight) of the smell particles and because the particles are individ-ually very small (in terms of weight and size), their initial situations and states of motion are not known. Even if this is known, there is an unequal power to the task of following the subsequent motion of all the individual smell molecules

[35]. Thus, the faith of individual smell molecules will not be the focus of the proposed smell agent optimization (SAO) algorithm but, on the collective distribution of properties and motion (diffusion) of these smell molecules. Fig.4 shows a typical random movement of a smell molecule. It can be

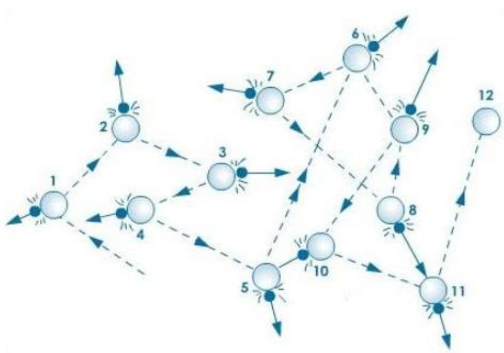


Figure 4. Random Movement of smell Molecule

observed from Figure 2 that, point 1 shows the initial posi-tion of the gas molecule. The molecule moves through all the other point until the destination point 12, in a Brownian form. The path followed by the gas molecule can thus be deduced as in Fig

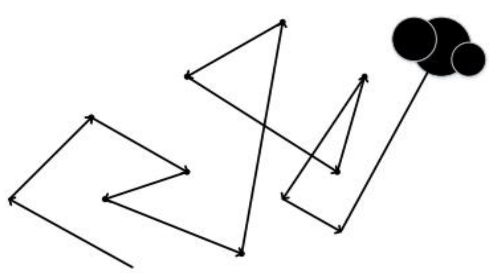


Figure 5. Smell Molecule Path Illustration

Trailing the path of the smell molecule shown in Fig.5 is usually the main focus of all smell agents. By this, virtually all organisms are aware of the presence of chemical substances in their environments and ensure their survival.

3 SMELL AGENT OPTIMIZATION (SAO)

Every biologically inspired optimization algorithms are usually based on a number of critical modeling parameters. These parameters are usually decided through careful obser-vation and understanding of the biological system on which the algorithm is inspired. In order to develop an algorithm which is inspired by the phenomenon of smell, the Brownian movement of the smell molecules towards the agent, the training movement of the agent towards the molecule should be considered. Thus, the following mode for the algorithm can be modeled.

a. The gaseous molecules of smell evaporate in the direction of the Smell Agent (SA). This is termed the sniffing mode.
b. The SA trailing the part of the gaseous molecules smell and eventually identify it source. This is termed the trailing mode.
c. In a situation where the agent loss its trail during the search, a position is selected randomly and the agent move towards this position hoping to sniff the smell molecule again. This is termed the random mode.

3.1 Sniffing Mode

In a practical situation, the agent should be able to sniff the smell particles and intuitively follow this particle with the hope of identifying its source. This usually bemuse the agent, due to variation in the temperature and molecular mass of the smell particles, making part trailing a challenging task. While exploring the search space, the concentration of smell molecules may become higher than the current position of the agent, in this case, the agent moves towards this position. This way, the agent continues to trail the position of all molecule with higher concentration until the molecule with the overall best fitness (smell source) is identified. This behavior of the agent would be model as the sniffing mode in smell agent optimization.

The process of SAO is initiated by a randomly generated initial position (population) of smell molecules. The size of the population depends on the total number of molecules of smell evaporating from the smell source. Assuming the smell molecule is denoted as N and the hyperspace where the smell molecule is evaporating is denoted as D, then, the population of the smell molecules will be assigned a position as

$$X_i^t = \left[X_{N,1}^t, X_{N,2}^t, \ldots, N_{N,D}^t \right] \quad (1)$$

where $\{i = 1, 2, ..., N\}$, t is the present position of a smell molecule. The position vector in eq.1 enables the agent to determine the region with the highest concentration in the search space. For example, consider the coordinate positions given in Fig.6 3. Each cycle in the cell depicts a molecule of smell. The number of columns in the figure represents the dimension (D) or solution search space to be explored while the number of rows represents the population of the smell molecule exploiting the search space. From Fig.6, if N is 3 and the index of the molecule with the highest concentration

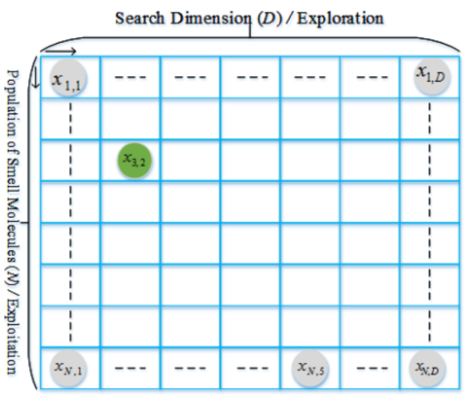


Figure 6. Smell Position in Hyperspace

is $x^t_{3;2}$, this indicates that the smell molecule with the highest concentration, in this case, is at the coordinate (3,2) of the entire search space indicated as a circle with green color. Since the smell molecule evaporates and travels through the air in the direction of the agent, each molecule can be said to maintain a uniform velocity in the direction of the agent, provided the intensity of the air medium is constant. This movement velocity of the smell molecule is denoted as V. The velocity-vector V is the diffusion vector (which is a displacement of the smell molecule from the smell source/origin). Thus, the position of the smell molecules considering the velocity vector will be given as

$$X_i^{t+1} = X_i^t + V_i^t \tag{2}$$

Since every smell molecules will their corresponding veloc-ities for which they move and update their position in the search space. The preliminary theory of molecules move-ment and the heuristic derivation of the velocity distribution function given by Maxwell in [36] will be used to develop the velocity update model

3.2 Trailing Mode

While exploring the search space, the concentration of a smell molecules may become higher than the current posi-tion of the agent, in this case, the agent moves towards this position. This way, the agent continues to trail the position of all molecule with higher concentration until the molecule with the overall best fitness (smell source) is identified. In practical situation, the agent should be able to sniff the smell particles and intuitively follow this particle with the hope of identifying its source. This usually bemuse the agent, due to variation in the temperature and molecular mass of the smell particles, making part trailing a challenging task. Also, every agent has a specific capacity of olfaction, depending on their size of olfactory lobe, psychological and physical condition. For example, larger size of olfactory lobe indicates a stronger olfaction which favors exploitation while smaller size of olfactory lobe indicates poor olfaction which is an indication of poor exploration. Since the proposed SAO is generalized for all agent, the SAO precision and convergence will obviously be influenced by the olfaction capacity of the agent. This behavior of the agent would be model as the trailing mode in smell agent optimization. The conceptual framework of the SAO is given in Fig.7.

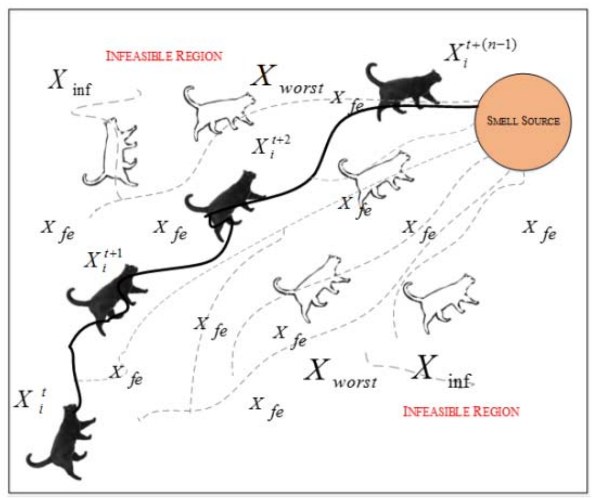


Figure 7. Smell Position in Hyperspace

In Fig.7., the agent is represented as a cat and the object evaporating the smell molecule is depicted in the grey circle. The dotted lines (labeled X) denote the direction of the evaporation of the smell molecules while the thick line represents the path with a high concentration of smell (optimum path). The paths labeled X_{fe} are all feasible paths (path with lower smell concentration) which if followed could lead the agent to the smell source. However, the agent is usually restricted to follow only the optimum path all through the search process. At every stage in the searching process, the agent takes note of the X_{worst} position (feasible paths in a generation) and makes use of this information to restrict its movement within the optimum path. This ideology will be modeled in the trailing mode search equation. The path labeled X_{inf} is an infeasible path, which leads the agent to an infeasible solution. The movement towards this region is avoided by appropriately selecting a suitable value for the SAO control parameters.

During the search process, the SAO identifies the region with high concentration of smell by performing the sniffing mode which represents the first position of the cat in Fig.7. The agent (cat) updates its position by performing the entire process of SAO and updating (iteratively) its position until the smell source is reached (optimum solution is obtained).

3.3 Random Mode

The smell molecules are discrete in nature if these molecules are separated by large distance apart in comparison with the molecular search dimension, the intensity/concentration of the smell molecule varied over time from one point to another. This bewilders the agent, and the agent may subsequently lose the smell, making the trail a challenge. At this point, the agent maybe trapped into local minimal leading to its inability to continue trailing. In the natural situation, the agent moves randomly within the smell perception region hoping to perceive the smell molecule again. This behavior of the agent will be model as the random mode in the smell agent optimization.

4. CONCLUSION

This report has presented a feasibility study towards the development of a novel Smell Agent Optimization (SAO) algorithm using the diffusion process of smell molecules and the trailing behaviours of an agent towards these molecules. The evaporation of smell molecules from the smell source and the Brownian motion of these molecules in the direction of the agent will be developed. Thereafter, the smell per-ception capability of the agent will be determined and the trailing behaviour of the agent towards the smell molecules as the agent seeks to identify the source of the smell will also be developed. In our future work, the SAO algorithm will be developed and its application to various combinatorial optimization problem will also be presented.

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