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Human Swarming with Artificial Swarm Intelligence using a hybrid approach

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Abstract - Swarm Intelligence explores swarms of autonomous robots or simulated agents. Little work, however, has been done on swarms of networked humans. Artificial Swarm Intelligence (ASI) strives to facilitate the emergence of a super-human intellect by connecting groups of human users in closed-loop systems modeled after biological swarms. Early studies have shown that "human swarms" can make more accurate predictions than traditional methods for tapping the wisdom of groups, such as votes and polls. *Artificial Swarm Intelligence* enables groups to form real-time systems online, connecting as 'human swarms' from anywhere in the world. A combination of real-time human input and A.I. algorithms, a Swarm *Artificial Swarm Intelligence* based system combines the knowledge, wisdom, opinions, and intuitions of live human participants as a unified emergent intelligence that can generate optimized predictions, decisions, insights, and judgments. Simply put, Swarm A.I. technology creates amplified intelligence while keeping humans in the loop.

Keywords*:* Swarm intelligence, Human Swarming, ASI Algorithms.

I. INTRODUCTION

Designing an artificially intelligent based systems, researchers [2] have historically turned to Mother Nature for guidance. Not surprisingly, the first model to be explored was the most familiar that is our own brains. Starting with perceptron of the 1950's and continuing to this day, neural networks and other neurologically inspired architectures are the dominant models for A.I. research. This said, nature is not a one-trick pony. Billions of years of evolution have produced at least one alternate method of building high-level intelligence and it is not neural it is collective.

With Swarm Intelligence (SI), nature shows us that by forming closed-loop systems among large groups of independent agents, high-level intelligence can emerge that exceeds the capacity of the individual participants. Researchers have explored this extensively for organizing groups of robots and simulated agents, but only recently have the principles of swarming been applied to humans.
Swarm intelligence is the discipline that deals with natural and artificial systems composed of many individuals that coordinate using decentralized control and self-organization. In particular, the discipline focuses on the collective behaviors that result from the local interactions of the individuals with each other and with their environment. Examples of systems studied by swarm intelligence are colonies of ants and termites, schools of fish, flocks of birds, herds of land animals. Swarm intelligence becomes more interesting when the parts appear to operate completely independently of each other, as with a swarm of honeybees finding a new home for the hive, or a school of fish swimming, or molecules in a cell generating life.[1].

Swarm intelligence becomes more interesting when the parts appear to operate completely independently of each other, as with a swarm of honeybees finding a new home for the hive, or a school of fish swimming, or molecules in a cell generating life.[1] Known as Artificial Swarm Intelligence. These systems enable human groups to work together in synchrony, forging unified systems that can answer questions, make predictions, and reach decisions by collectively exploring a decision-space and converging on preferred solutions. Prior studies have shown that by working together in real-time, human swarms can outperform individuals as well as outperform traditional methods for tapping the wisdom of groups such as polls, votes, and markets. A study in 2015 on a tasked a group of human subjects with predicting the top 15 awards of the 2015 Oscars. This was performed both by traditional poll and real-time swarm. Among 48 participants, the average individual achieved 6 correct predictions on the poll (40% success). When taking most popular prediction in the poll (across all 48 subjects), the group achieved 7 correct predictions (47% success), a modest increase. When working together as a real-time swarm, the group achieved 11 correct predictions (73% success) [Rosenberg, 2015]. This suggests that human swarming may be a superior method for tapping the wisdom of crowds.

II. LITERATURE REVIEW

A literature Review was conducted to analyse the Human Swarming find the real time accurate of results obtained by using the unified platform by the human swarming algorithms. Rosenberg, L. (2016) performed a work to expose and explore the different paradigms of finding the accurate predictions than traditional methods. To further test the predictive ability of swarms, 75 random sports fans were assembled in the UNU platform for human swarming and tasked with predicting College Bowl football games against the spread. Expert predictions from ESPN were compared. The results are as follows: (i) Individuals – when working alone, test subjects achieved on average, 5 correct predictions out of 10 games (50% accuracy); (ii) Group Poll – aggregating data across all 75 subjects, the group achieved 6 correct predictions out of 10 games (60% accuracy); (iii) Experts - as published by ESPN, the college football experts averaged 5 correct predictions out of 10 games (50% accuracy); and (iv) Swarm – when the 75 subjects worked together as a real-time swarm, they achieved 7 correct predictions out of 10 games (70% accuracy). Thus by forming real-time swarm intelligence, the group of random sports fans boosted their collective performance and out-performed experts. [2] Rosenberg, L. (2015) explained in his paper about the new platform called UNUM that allows groups of online users to collectively answer questions, make decisions, and resolve dilemmas by working together in unified dynamic systems. Modelled after biological swarms, the UNUM platform enables online groups to work in real-time synchrony, collaboratively exploring a decision-space and converging on preferred solutions in a matter of seconds. We call the process "social swarming" and early real-world testing suggests it has great potential for harnessing collective intelligence. [3] Beni, G., et al. (2016) explained the swarms as the intelligent systems that are used to find the accurate result. This paper introduces UNU, an online platform that enables net-worked users to assemble in real-time swarms and tackle problems as an Artificial Swarm Intelligence (ASI). Early testing suggests that human swarming has significant potential for harnessing the Collective Intelligence (CI) of online groups, often exceeding the natural abilities of individual participants. [1] Rosenberg, L. (2016) discussed about the concept of swarm intelligence and Hive mind in them. A hive mind or group mind may refer to a number of uses or concepts, ranging from positive to neutral and pejorative. [9] Zhu, f. Yan, et al. (2010) discussed a broad overview of swarm intelligence in three parts: biological basis, artificial literature and swarm engineering. In biological basis part, the paper gives some operational principles from biological systems by naturalists and biologists. In artificial literature part, two fundamental approaches are provided to analyze swarm topology. The prevalent swarm models and techniques such as Reynolds's rules, discrete and continuum theory of flocking, coordination stability of the swarm motion, etc., are also summarized in this part. In swarm engineering part, the paper discusses Kazadi's "twostep" process. Many engineering applications come from Kazadi's researches. Also, the main application of swarm intelligence on robot systems and other applications are introduced in this part. We say this paper provides concepts for a better understanding of swarm intelligence both in principles and in applications. [10]

Seeley, Thomas D. (2010) explained in his book about the decision making strength of honeybee. He discussed about the facts that honeybees make decisions collectively—and democratically. Every year, faced with the life-or-death problem of choosing and traveling to a new home, honeybees stake everything on a process that includes collective fact-finding, vigorous debate, and consensus building. In fact, as world renowned animal behaviourist Thomas Seeley reveals, these incredible insects have much to teach us when it comes to collective wisdom and effective decision making. A remarkable and richly illustrated account of scientific discovery, Honeybee Democracy brings together, for the first time, decades of Seeley's pioneering research to tell the amazing story of house hunting and democratic debate among the honeybees. In the late spring and early summer, as a bee colony becomes overcrowded, a third of the hive stays behind and rears a new queen, while a swarm of thousands departs with the old queen to produce a daughter colony. Seeley describes how these bees evaluate potential nest sites, advertise their discoveries to one another, engage in open deliberation, choose a final site, and navigate together--as a swirling cloud of bees--to their new home[5]. Seeley ***et al***. investigates how evolution has honed the decision making methods of honeybees over millions of years, and he considers similarities between the ways that bee swarms and primate brains process information. He concludes that what works well for bees can also work well for people: any decision making group should consist of individuals with shared interests and mutual respect, a leader's influence should be minimized, debate should be relied upon, diverse solutions should be sought, and the majority should be counted on for a dependable resolution. An impressive exploration of animal behaviour, Honeybee Democracy shows that decision-making groups, whether honeybee or human, can be smarter than even the smartest individuals in them. Seeley, Thomas D., et al. [6] (2012) has compared the relationship between the Honeybee swarms and complex brains and how they make decisions. In both, separate populations of units (bees or neurons) integrate noisy evidence for alternatives, and, when one population exceeds a threshold, the alternative it represents is chosen. An analytic model shows that cross inhibition between populations of scout bees increases the reliability of swarm decision-making by solving the problem of deadlock over equal sites. I.D. Couzin (2008) [19] has discussed about the collective collective action of organisms such as swarming ants, schooling fish and flocking birds. This interdisciplinary effort is beginning to reveal the underlying principles of collective decision-making in animal groups, demonstrating how social interactions. It is proposed that important commonalities exist with the understanding of neuronal processes and that much could be learned by considering collective animal behaviour in the framework of cognitive science. Seeley, Thomas D., ***et al.*** (2003) [4] has explained the group decision making policy of honeybee. In this study, the concept of new site selection by the honeybee is explained. This study considers the mystery of how the scout bees in a honey bee swarm know when they have completed their group decision making regarding the swarm's new nest site. More specifically, we investigated how the scouts sense when it is appropriate for them to begin producing the worker piping signals that stimulate their swarm mates to prepare for the flight to their new home. Varinder Singh ***et.al***.[23] in tested two hypotheses: "consensus sensing, ^ the scouts noting when all the bees performing waggle dances are advertising just one site; and "quorum sensing," the scouts noting when one site is being visited by a sufficiently large number of scouts. their test involved monitoring four swarms as they discovered, recruited to, and choose between two nest boxes and their scouts started producing piping signals. They found that a consensus among the dancers was neither necessary nor sufficient for the start of worker piping, which indicates that the consensus sensing hypothesis is false. They also found that a buildup of 10-15 or more bees at one of the nest boxes was consistently associated with the start of worker piping, which indicates that the quorum sensing hypothesis may be true. In considering why the scout bees rely on reaching a quorum rather than a consensus as their cue of when to start preparing for liftoff, they suggested that quorum sensing may provide a better balance of accuracy as well as speed in decision making. In short, the bees appear to begin preparations for liftoff as soon as enough of the scout bees, but not all of them, have approved of one of the potential nest sites.

Karasi, A., et al. (2016) proposed the methods for finding the best location. In this work, a model - which uses SI through the behaviour of Ants, is proposed. The model can be used to find safe paths to safe locations in such disaster-affected areas where the state rescue and relief teams may take some time to reach. The information generated by stranded victims or people, who have somehow managed on their own to reach safe locations, is used to find paths that can be suggested to other agents stranded in the disaster-affect areas. This is done through mobile-phones via web enabled services. The technique allows a large number of people to reach the safe locations on their own, which aids the ongoing state rescue and relief operations. Paths created by following the GPS log traces can be used to make new paths which are the hybrids of the previous paths created. Real life constraints will be considered such as capacity of safe areas, paths etc. [11]

From the literature review conducted the accuracy level can be further improved by combining the results of human experts as well as the results of ASI algorithm. Better results can be obtained if it is run on a UNU based platform.

III. PROBLEM FORMULATION

Presently unified platform was used to find the real time accurate result in human swarming algorithms. In that the real time human decision is taken through the real time platform and finds the best optimum result.

In our work so as to improve the accuracy level we are trying to propose a novel hybrid algorithm by combining the results of ASI algorithm running on UNU based platforms with both the human experts and artificial swarm intelligence algorithms. UNU being an open platform that enables networked users to assemble in online swarms and tackle problems as an *Artificial Swarm Intelligence* (ASI). In the new platform the real time decisions from the humans will be captured. Here the result from the ASI algorithms will be merged with the ratio to find the optimal real time result that will give the accurate result than the all other proposed algorithms.

IV. Objective

Is to design a novel architecture in swarm intelligence so that more accuracy can be achieved.

V. Conclusion

This project work is an approach to find accurate result by designing a novel hybrid algorithm that combines the results of ASI algorithm running on UNU based platforms with both the human experts and artificial swarm intelligence algorithms. This could lead to the development of a super-intelligence system that can produce more accurate results.

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