CHARACTERIZATION of SWARM BEHAVIOR THROUGH PAIR-WISE INTERACTIONS by TSALLIS ENTROPY

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Abstract - This paper tries to look at the interactions of a swarm of two at an elementary level. The change in the swarm entropy during the interactions is investigated. The characterization of swarm behavior has been subsumed in four modes, i.e. normal-free, normal-swarm, feeding and obstacle modes. Based on these modes, an entropy based algorithm is constructed to observe pair-wise interactions for each mode. For these modes, individuals of swarm are taken into account as self-driven interacting particles in the mathematical model. Statistical entropy definitions are used to control individual's behavior in feeding and obstacle modes. Individuals lose interactions enabling swarm behavior in feeding mode because of the priority of feeding for individuals as in nature. On the other hand, when swarm confronts an obstacle, individuals interact as much as they can. However they may lose interaction, depending on the size of the obstacle and position of the individuals. For feeding and obstacle modes, it is observed that Tsallis Entropy fits in the simulation better than other entropy definitions such as Shannon and Renyi.

Keywords: Swarm Intelligence, Distributed Behavior, Tsallis Entropy, Pair-wise Interactions

1. INTRODUCTION

Fish, bees, ants and many other creatures in nature form swarms and their behaviors are observed for creating better simulations of a swarm behaviour. According to the observations , swarms do not have a leader. Instead of centralized control, there are some local rules within the swarms [1]. The study of Y.Inada [2] was aimed at analyzing steering mechanisms of fish schools. According to Inada, the principle of collective motion behavior of fish schools was led by the neighborhood relationship between the swarm individuals. Furthermore, the social insect (i.g. beer, ant) behavior was modeled and simulated according to pair-wise interactions in the study of Moran [3]. Especially, insect social life was classified into three modes: cruise, protection and feeding. Moreover, in the study of D. Woxman, it was stated that the ant swarms undergo a translation between disordered state to ordered state in the feeding condition [4]. The neighborhood relationship in swarms was also realized in aggregative behaviors by Boi et. al. [5]. In the study of Hubbard et. al., [6], migration was investigated in addition to three modes stated in Moran's study [3]. It was stated that the fish schools showed collective behavior in migration that caused by neighborhood relationships.

Nature already provided good solutions to manage groups of less able beings; fish schools, ant swarms, animal packs, bird flocks and so on. With the growing desire of humans to create intelligent systems, these bio-systems are thoroughly being inspected [7..15] and implemented [2,5,6,16..21] in various studies such as robot applications and optimization.

Swarm behavior of pair-wise interactions was modeled. Simulations were constructed with four modes, normal-free, normal-swarm, feeding and finally obstacle modes. Simulation is started with normal-free mode. In this mode, two individuals have different positions in the simulation area. During the free mode, individuals move with random direction and velocity. Moreover, individuals stay in free mode up to a certain displacement between individuals. After this certain displacement, these individuals start behaving as a swarm. This swarm behavior is called as normal-swarm mode in the algorithm.

2. Pair-wise Entropy-based Modeling

Interactions between the swarm individuals (drones) will be examined at an elementary level. These interactions will be characterized by different forms of entropies so as to compare eventual performances. Pair-wise modeling was selected since a swarm is formed when as little as two drones are combined. Similar to the swarm behavior modes explained earlier, another four modes are created not only to simplify the problem but also to match the modes to a two-drone swarm. Normal-free, normal-swarm, search-feeding, and obstacle modes are defined for the whole simulation of the swarm. Each mode was devised for controlling individuals in specific cases.

2-3-1. Entropy Control

Definition of Entropy, which was firstly found by Boltzmann, can be given as a measure of disorder. There are many types of entropy definitions in the literature. One of them is Tsallis entropy first explained in 1988 [22]. Tsallis modified the mathematical expression of entropy definition given by both Shannon and Boltzmann in his study and defined a new parameter, q (see equation (1)).

Shannon, Renyi and Tsallis entropy definitions were implemented to investigate the swarm behavior in this study. It is seen that Tsallis entropy desrcibe the swarm behavior more realisticly than other entropy definitions.

$$S_T = \frac{1 - \sum_i P_i^q}{1 - q} \tag{1}$$

Here P_i is the probability of being a swarm for each individuals and q is a real parameter, which ranges from 0 to 1. As q approaches 1, Tsallis entropy term becomes the Boltzman-Gibbs entropy term which is known as classical entropy term. In our study, real parameter was taken as 0.5 for simulation. Also two different Gamma probability distributions were used for characterization of probability of each individual. General Gamma distribution was expressed as [23];

$$P_i(X) = \frac{1}{\Gamma(X)\beta^{\alpha}} X^{\alpha-1} e^{-X/\beta} \tag{2}$$

In Gamma distribution, α and β are parameters and X is defined by case dependent variable, for example in normal -free and -swarm mode, case dependent variable was taken as relative displacement, R/R_p, ratio of displacement between individuals and radius of parallel orientation field due to maximum probability of being a swarm occurs at the edge of the parallel orientation field (R_p). Therefore, α and β were chosen as 2 and 1 respectively.

However, probability must be different for feeding and obstacle modes due to the disturbances to individuals. Therefore, probability was defined with displacement between feed or obstacle and each individual in feeding and obstacle mode. In other words, probability of feeding or detecting an obstacle decreases when displacement increases. Thus, for simulation both α and β were chosen as 1 and probability distribution was given in Fig. 1.

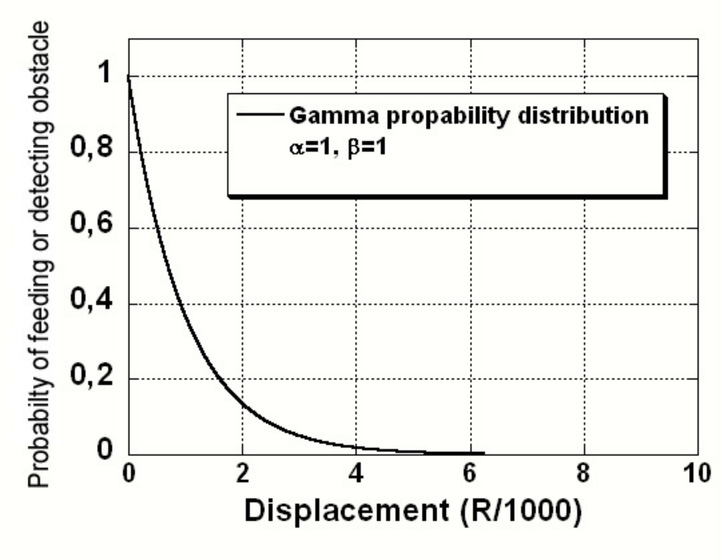


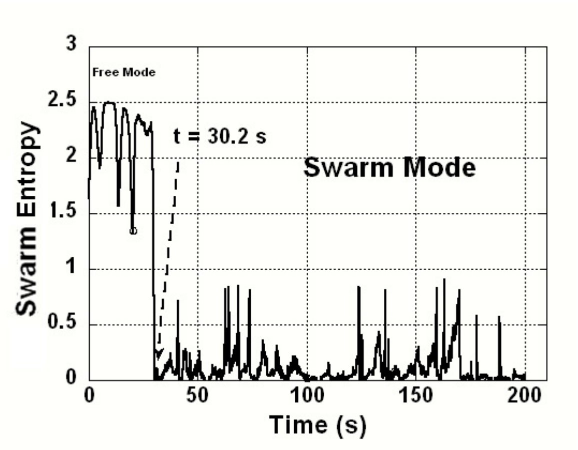
Fig. 1. Probability distribution for feeding (or obstacle) mode.

Change of Entropy in normal and feeding (or obstacle) modes was drawn with respect to probability distribution. It is understood from each graph, entropy has the highest value when the probability distribution is close to zero. Also entropy is zero when probability values are equal to 1. This shows that individuals of the system choose the event that leads to a state of low entropy. Therefore chosen probability functions are very suitable in simulation of pair wise interactions in swarm behaviour.

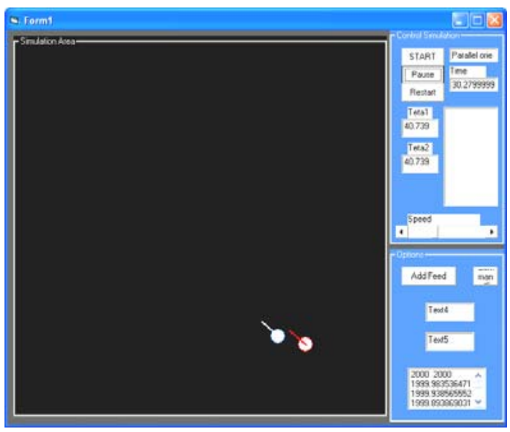
3. Results and Discussion

In normal-free mode, entropy exhibited high values because of the large distances between individuals. However, a decrease occurs, when the individuals approach each other. Furthermore, if an individual enters in the repulsion field, entropy increases and stability decreases. Therefore, each individual moved with random direction and velocity. None of the individuals could detect each other until the distance was in the detection range of indvidual, Fig. 2.

Fig. 2 shows a transition from high entropy high disorder state to an ordered low entropy one. At this time, entropy steeply decreased, and oscillated in lower values, depending on the individual movements.



(a)

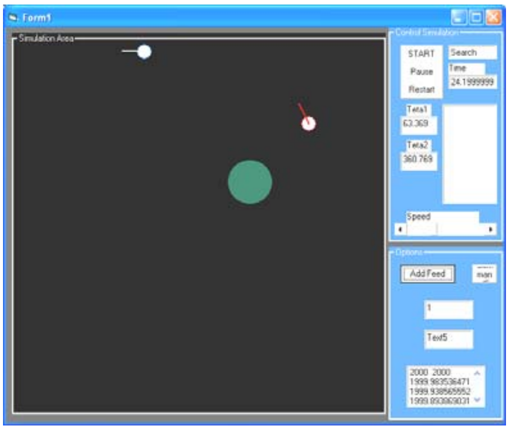


(b)

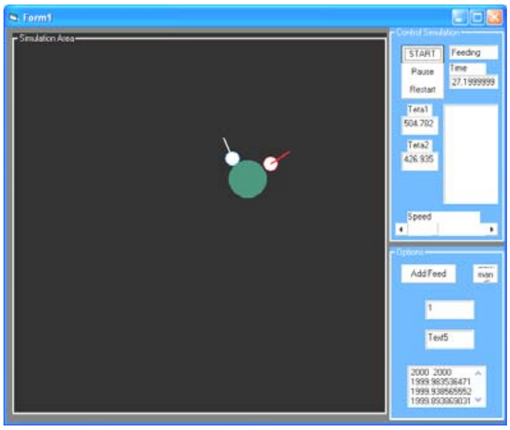
Fig. 2. (a) Entropy changing for normal-swarm mode, (b) Individual positions in normal-swarm mode t = 30 s.

Peaks in entropy of swarm mode were created by attractive and repulsive behavior of individuals. As it was programmed, individual velocity was changed by program randomly. So, if the individual ahead has randomly higher velocity than the one behind, distance and the entropy increase. In this case, the front one turns toward the other for sustaining swarm behavior, thus decreasing the entropy. This explains how the attraction procedure works.

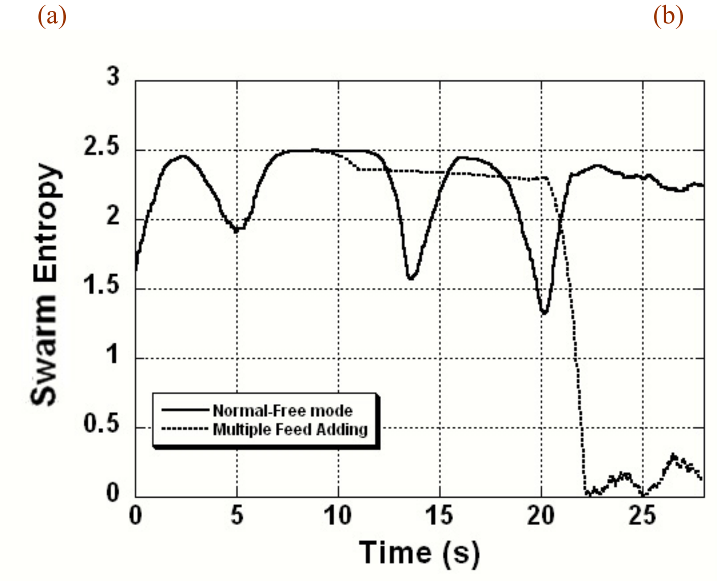
Swarm behavior was continuously maintained by individuals until some type of disturbance appeared. Feed or obstacle which is on the path of moving direction of the swarm can disturb the system. For example when a feed was added in the simulation area in free mode, individuals were directed toward to feed and when individuals reached the feed, they started to bite it, Fig. 3. (a), (b), total entropy also was steeply decreased Fig. 3 (c). This was simply because individuals approach the feed and each other. Moreover, in the absence of feed or obstacle, individuals moved in swarm mode.



(a)



(b)



(c)

Fig. 3. (a) One feed adding in normal free mode, (b) individuals response, (c) entropy changing.

For examination of the change in the swarm entropy in normal-swarm mode, three trials of feed adding were achieved at same time period. It was found that in normal-swarm mode, swarm entropy did not change drastically with one feed adding. Only a few peaks were observed during the feeding mode, these were probably caused by the algorithm that enables individuals not to touch each other while they were approaching the feed.

4. Conclusion

In this work, swarms have been dealt with. Pair-wise interactions are studied by statistical entropy (Tsallis) for four modes. These are normal-free, normal-swarm, feeding and obstacles modes. It is observed that entropy tends to oscillate in small values for the normal-swarm mode; however entropy oscillates in high values for normal-free mode. It is also seen that attractive and repulsive behavior of individuals creates peaks in the entropy of the swarm mode due to small changes in distance. In the case of adding multiple feeds, individuals select the nearest feed, lowering the entropy as in nature. In obstacle mode, individuals move around the obstacles to reach feed when feed is added at the same time. Again, the entropy decreases while individuals are closing in. Briefly, when feeds and obstacles are added, individuals can move apart from each other. This study has shown that local simple rules may have great consequences in the global scale. Therefore any swarm simulation or work must account for the interactions at small scales to present and apply effective control strategies. More effect-and-cause simulations must be carried out both locally and globally to enhance the control of simulations.

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