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A honeybee social foraging algorithm for feedback control of smart lights

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ABSTRACT

In contrast to the wide array of research that uses swarm intelligence to solve optimization problems, a few approaches have recently been taken a feedback control perspective as we do here. To employ a feedback control approach, this paper shows that an algorithmic model of how honeybees forage can be used for control of smart lights. We show that only slight modifications to this model are needed to control multiple lights and to provide uniform illumination across the floor of an experimental testbed. The most challenging case is when there are no walls between lighting zones since then there are a significant inter-zone couplings, and the approach here performs especially well under these conditions. Performance of this method is compared with a variety of testbed conditions where we assume inter-zone coupling as overlapping sources. Experimental results supported by parametric statistical tests suggest that the method here is better when significant overlapping is addressed.

1. Introduction

Smart light systems attempt to guarantee an efficient use of energy, i.e., to reduce energy consumption and to prevent energy waste (Ciabattoni et al., 2013; Suzdalenko et al., 2012; Martirano, 2011; Husen et al., 2011; Bhardwaj et al., 2011; Miki et al., 2004). However, the energy waste due to cross-illumination (also called over illumination) is not addressed. Cross-illumination occurs due to multiple artificial lights in the ceiling and/or daylight penetrating the room. In a shared-space office, a light bulb illuminates not only the cubicle under it but also the rest of the nearby cubicles. Thus, the cross-illumination effect in an area is the light level received for the contribution of lights from bulb lights surrounding this (Koroglu and Passino, 2014). Similar to Schultz (2009), Koroglu and Passino (2014), and Velasquez and Passino (2015), we view cross-illumination effects as ones that provide an opportunity to reduce energy consumption and prevent energy waste. We use the smart lights experimental testbed designed and developed by Schultz (2009) where the cross-illumination effects depend on the experimental environment setup. Thereby, if the experimental environment is using a full partition setup the cross-illumination effects will be minimized, but when all the walls are removed we confront the most challenging cross-illumination effects. This particular smart lights experimental testbed allows a number of interesting control challenges starting with the non-uniform illumination of the different zones; it is clear that different zones will elicit different responses from the same control law (Schultz, 2009). However, each zone of the testbed seems to act like a first order system with a delay and saturation, but a significant and unpredictable coupling between the zones, since each bulb illuminates multiple neighboring zones. These features turn the smart lights experimental testbed into a complex system where distributed control algorithms can be evaluated mainly.

Schultz (2009) developed a distributed proportional-integral (PI) controller which has been successful achieving uniform lighting across the testbed but not for the case where the cross illumination effects are maximized between the light sensors; the author also evaluated an algorithm based on the study of flight guidance in honeybee swarms solving a distributed agreement problem to nest-site selection with similar results; however, its unsuccessful performance proves how crucial the cross-illumination effects are. Later, other distributed control strategies have been implemented in the testbed which achieved uniform lighting across all room partition settings. These strategies include the so-called illumination balancing algorithm (IBA), inspired by load balancing in processor networks with communication between neighboring zones, being combined with an integral

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controller to achieve the uniform lighting for all cases (Koroglu and Passino, 2014) and the fuzzy fault tolerant controller (Velasquez and Passino, 2015) one that shows that without communication it is still able to adapt itself to uncertainties such as disturbances and light and sensor failures.

Here, we use the smart lights experimental testbed of Schultz (2009) with eight inputs and eight outputs to implement a bio-inspired feedback controller based on honeybee social foraging. Due to the complexities in the testbed, it has not been possible to develop an accurate mathematical model for the experiment, and hence not possible to use classical "model-based control" methods (Velasquez and Passino, 2015). On the other hand, when a bio-inspired feedback controller is implemented, some analogies between the swarm behavior and the control goal might be enough to take the place of the lack of mathematical model from any experimental system based mainly on adaptive resource allocation as it has been shown by Marulanda et al. (2013), Quijano and Passino (2010), Quijano et al. (2006), and Passino (2002). Since a mathematical model is not available, a bio-inspired algorithm based on honey bee social foraging presented by Passino and Seeley (2015) is selected and implemented as a candidate control strategy, something that has not been considered in the literature on smart lights. Similar to Quijano and Passino (2010), we assume that there are a fixed number of bees involved in the foraging process where each bee corresponds to a quanta of energy and the foraging landscape is composed of eight forage sites which represent the zones in the experimental testbed. Also, the error (i.e., the difference between the desired value and the amount of brightness in the zone) is considered as the profitability on the forage site. Then, we show that an algorithmic model of social foraging of honey bees with slight modifications can be used for reference tracking and can achieve uniform lighting across the entire floor of the experimental testbed even when the cross-illumination is maximized between neighboring zones. We refer to this modified algorithm as the Honeybee Social Foraging Algorithm (HSFA).

We face the cross-illumination effects on the experimental testbed as the bees get the profitability from combined flower fields: on a natural landscape each patch of flower has similar profitability (Seeley, 1986), but its distribution in this field is not necessarily well defined (i.e., it could be combined with others). The bees take the nectar or load from multiple flowers around their current position on the flower fields. Although the honey bees in the hive had correctly been informed about the forage patch quality, these can arrive to combined flower fields because of imprecision during the waggle dance run (Weidenmüller and Seeley, 1999; de Vries and Biesmeijer, 1998). The whole profitability in the landscape will be reduced as the bees are draining the nectar either in an isolated patch or in a combined one. But, in combined flower fields, the bees get different portions of each patch as a combined profitability while in isolated flower fields, the bees only get the profitability from a particular patch. In HSFA, we assume a landscape with eight different forage patches which will be combined in three configurations: without overlapping, slight overlapping, and significant overlapping. Besides this, we have made four observations:

1. The bees evenly allocate their foraging workforce from the combined patches in the hive to allow us to determine how each patch is being deteriorated.
2. The bees from combined patches are transmitting the mean profitability information.
3. A particular storage comb in the hive is necessary to separately deposit the loads of each patch which provides information about the amount nectar gathered.
4. On the smart light experimental testbed this amount of nectar gathered will be associated with the amount or intensity of light in each zone.

Thus, we assume that these combined flower fields are comparable to the cross illumination effects in the smart light experimental testbed since the loaded profitability portion for each bee has to be distributed. Our approach seeks to illustrate how the performance in the testbed can be improved when the cross illumination effects are treated as combined flower fields, where the bees in the hive skillfully choose "good" spots among these patches, resulting in combined profitability rather than show the behavior when each parameter in HSFA is changed.

This paper presents an application of swarm intelligence for illumination tracking via feedback control of a smart lights system. The implemented HSFA has been able to accurately achieve uniform lighting across the entire floor of the experimental testbed under different testbed settings and particularly for the no-partition case when cross-illumination is maximized. Here, we have proposed the use of swarm intelligence on a real physical experiment instead of other engineering applications of swarm intelligence that are mainly focused on simulations. Despite the honey bees' social foraging behavior in the hive being a decentralized system because it does not need a centralized entity for both the decision-making and forage allocation process (Seeley, 1996), our approach needs a global information about the error signal and the number of waggle dance runs to avoid a kind of over-exploitation of sites or overshoot in control, and to maintain an available work force when new sources are found or old ones have improved their profitability.

Therefore, a centralized control approach where the control effort is centrally computed and then applied throughout the eight independent zones (unlike of Koroglu and Passino, 2014; Velasquez and Passino, 2015) is proposed. This eliminates the need for implementing eight separate controllers on each zone. Furthermore, we do not need to extensively tune the controllers (as in Koroglu and Passino, 2014; Velasquez and Passino, 2015) to obtain good overall system performance. The advantages of our approach are the following: first, a good transient response and smaller overshoots or undershoots when present, and second, improved uniform lighting under the no-partition case, something that the decentralized integral control failed to do and for which Koroglu and Passino (2014) showed poor tracking performance.

This paper is organized as follows. Section 2 presents background about smart lighting systems and feedback control with swarm intelligence. In Section 3, a detailed description of the experimental smart lights testbed is given. Section 4 presents the model of a honeybee colony foraging for nectar proposed by Passino and Seeley (2015). In Section 5, the HSFA is explained, including the decision-making process, the proposed modifications to do reference tracking as a feedback control problem, and the parameters. In Section 6, implementation results are presented which include results from achieving uniform illumination tracking for three different reference inputs as well as the effect of changing the "radius of sites" in the emulated testbed landscape. In Section 7, the conclusions are provided.

2. Background

2.1. Smart lighting systems

Smart lighting systems seek the optimal use of lighting to save energy, decrease cost, reduce environmental impact (reduction of CO_2 and SO_2 emissions), and give maximum comfort to users. Lighting is one of the largest electrical end-uses after electric motor-driven systems. It requires as much electricity as is produced by all gas-fired generation and 15% more than produced by either hydro or nuclear power; until 2009, lighting has been responsible for about 19% of worldwide electricity consumption and it is estimated that the global