A Hybrid Simulation Model for Moving Objects

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ABSTRACT: Following a discussion of the strengths and weaknesses of the current modeling paradigms used for movement simulation in movement ecology, a hybrid simulation model is proposed that jointly exploits the benefits offered by agent-based models (ABM), discrete event simulation (DES), and system dynamics (SD), respectively, while attempting to limit their drawbacks. We describe the transition from a conceptual model of movement to the logical structure that is able to support the hybrid simulation model. We use examples from ornithology to instantiate the components of the logical model. Compared to traditional movement simulation methods such as correlated random walk, the proposed model can provide a more holistic representation of the movement of objects within their environment, while also maintaining the perspective of the individual object. We argue that this multi-level approach and flexibility is possible through the combination of the capabilities of ABM to model interactions among individuals, with the strengths of DES to model discrete events and global rules, and finally with the capacity of SD to model causality and feedback loops. Additionally, the motivation of an individual, being a core driver of movement, has been embedded into the logical simulation model.

KEYWORDS: movement simulation, movement ecology, agent based modeling, discrete event simulation, systems dynamics

Introduction

In a world where "all entities move and nothing remains still" (Heraclitus) geospatial simulation of movement is becoming increasingly important, not only for behavior forecasting and decision-making but also for assisting in better understanding of movement itself. The purpose of simulation experiments is threefold. It may be used to understand the behavior of the system, to evaluate strategies for the operation of it (Smith et al., 1998), or to actually formalize the existing knowledge and understanding of a behavior that is expressed through movement. In this case simulation of movement is a way to represent knowledge about movement along with enabling the user to control a simplified abstraction of reality.

Over the past decades, three fundamentally different paradigms have been developed for the simulation of dynamic processes (Borshchev et al., 2004): discrete event simulation (DES), agent based modeling (ABM), and system dynamics (SD). Each of these paradigms has its strengths and weaknesses, and thus they co-exist today in many simulation applications in diverse fields, used according to their particular properties.

In movement simulation in ecology, the prevailing model so far is the random walk model, which can be seen as a (simple) representative of the agent based model, and which exists in several variants, ranging from simple random walk to more complicated forms, such as Levy walks and Brownian bridges (Horne et al., 2007). A closer look at the requirements of movement simulation, however, reveals that movement is more complex than what random walk models can deliver. Modeling movement entails not only modeling the moving object and its locomotion, but also interactions with its environment (Nathan et al., 2008). Environmental conditions may change over time, and the movement process may exhibit different patterns at different spatial and temporal scales. All of this taken together suggests that probably, one paradigm is not enough to generate a *realistic* simulation of movement trajectories.

The objective of this paper, therefore, is to propose a hybrid simulation model that attempts to combine the advantages of the above three basic simulation paradigms, and exploit these in movement simulation. Using more than one simulation paradigm, it will be possible to implement movement simulations that represent the elements of comprehensive movement simulation models such as the one by Nathan et al. (2008).

Background and State of the Art

Conceptual Models of Movement

When trying to simulate the movement of one or several objects moving in an environment, it helps to first conceptualize the elements of the movement process. A review of conceptual models of movement could go as far back as Aristotle and his "On the Motion of Animals" (4th century BC), and Aquinas (13th century AD), but to be brief we restrict the discussion to the model proposed by Nathan et al. (2008). They conceptualize a focal individual (i.e. a moving object) that moves about in an environment. The individual (e.g. an animal) is firstly characterized by an *internal state* that provides the reasons why to move (e.g. the animal might be hungry, and moves to find food). Secondly, the individual has some *motion capacity* that defines how it can move (e.g. max speed, max duration of movement etc.). And thirdly, it has some *navigation capacity*, that is, the ability to sense its environment and orient in space and time, making decisions about when and where to move (e.g. locate and move towards a food source). The movement of the focal individual is influenced by *external factors* that affect the individual's capacities and internal state, and hence the *movement path* it takes.

Though relatively simple and compact, the model by Nathan et al. (2008) is also comprehensive, encompassing the key elements of the movement process. It thus has very quickly developed into a favorite framework within movement ecology, and also forms the foundation from where we develop our own work.

Movement Simulation Paradigms

Significant research has been conducted in the field of simulation of movement focusing on both animate and inanimate moving objects. After the suggestion of the classic 2D random walk (RW) for modeling animal movement (Turchin, 1998), an increasing number of external and internal factors have been incorporated into simulation models. Most of them come from older variations of RW, mainly implemented in the field of finance.

Some examples, representing movement behavior, are correlated random walk (CRW, Goldstein, 1951), self-avoiding random walk (Fisher, 1966), random walk with drift etc.

Three paradigms are commonly used in simulation: Agent Based Modeling (ABM), Discrete Event Simulation (DES), and System Dynamics (SD). In the following, we will provide an introduction of these paradigms and discuss their strengths and weaknesses.

Agent Based Modeling (ABM)

Agent Based Modeling is an increasingly used approach in movement simulation (Brown et al., 2005; Parker et al., 2002; Tang et al., 2010). Enhanced by the capabilities of GIS and geostatistics, ABM is able to express not only the moving part of the simulation but also the complex dynamics of ecological and social systems (Bousquet et al., 2004; Parker et al., 2002; Railsback, 2001). Implementations of ABM vary significantly, rendering a single definition of an agent inadequate. Here, an agent is seen as an algorithmically definable entity, with (Figure 1):

1. Internal state: the sum of all the attributes describing the agent.

2. Interaction with environment: the type of interaction with the external factors, incl. reactive, proactive and passive.

3. Interaction with agents: describes various social behaviors, such as collective, competitive behaviors etc.

Note that the above elements of an agent to some extent resemble the elements of the conceptual model of movement by Nathan et al. (2008).

Control of agent behavior in ABM has three *key properties* that clearly set ABM apart from the other simulation paradigms (Crooks & Heppenstall, n.d.):

- *Autonomy*: ensures decentralized control of the simulation. An agent is 'free' to interact with other agents and its context – without being manipulated directly by the user.

- *Heterogeneity*: agents might have similar or different, collective or non-collective behavior; they are created bottom-up, depending on the characteristics of each agent.

- *Activity*: agents are usually active in a simulation. They can be proactive, reactive, interactive, rational oriented, mobile, adaptive etc. That is, agents can follow a predefined logic, act together in a multi-agent system, perceive their context or not, and even have some memory and learning capacity in their behavior.

Limitations of ABM: Stating rules for each and every feature of the agent limits the feasible complexity in terms of the computability of the overall system. Certain emerging behavior that results from interactions among agents cannot be represented with a bottom-up approach alone. Furthermore, the spatial dimension of the paradigm involves poor handling of boundary conditions, and no inherent structure within geographic space

(Gilbert et al., 2002; Gahegan et al., 2005). Overall, however, for the task of movement simulation ABM does represent the most flexible approach among the three paradigms.

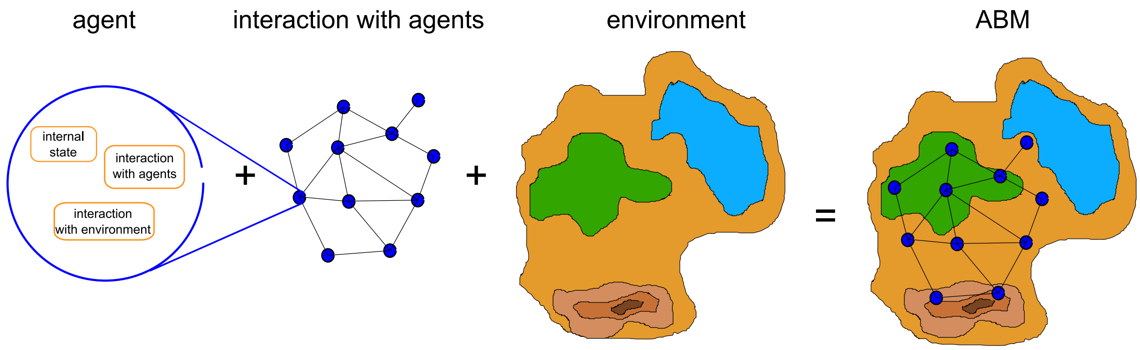

Figure 1: An agent based modeling example

Discrete Event Simulation (DES)

In DES the ‘event’ is considered to be the main focus of the modeler. Specifically, the DES consists of *entities*, *events*, *activities* and *processes*. An *entity* has attributes and is capable of changing its state. An *event* is everything that somehow changes the state of an entity. The *activity* describes the things that happen to an entity for a fixed time span, and a *process* is a list of events, activities and delays that define an entity in its lifecycle. The basic components and the flow of the simulation can be described by block charts, queues, delays etc. and resource sharing (Borshchev et al., 2004). The logic behind the operation of DES follows the familiar convention of the standard queuing model (Melamed et al., 2001) – one event takes place only after the previous one is finished, typically in a first-in first-out (FIFO) order, like clients in a bank waiting in a queue to be serviced by the cashier.

The logic flowchart in the traditional DES approach consists of a discrete chronological sequence of events, which in combination express an activity (e.g. in Fig. 2 Events 2 and 4 define Activity A), with instants in time when a defined state of a variable changes, *aka* an event (Robinson, 2004). The inherently ordered structure of DES makes it an appropriate tool to represent a system on an operational level (Morgan et al., 2011).

Limitations of DES: The nature of this paradigm leaves little room for developing simulations of individuals intuitively. It focuses on events, and not on the behavior of each individual. Thus, it can be very effective in sequential, queuing type simulation tasks. However, if optimization is required, one can merely repeat the simulation multiple times, changing parameters manually, waiting to see some variation in the model result.

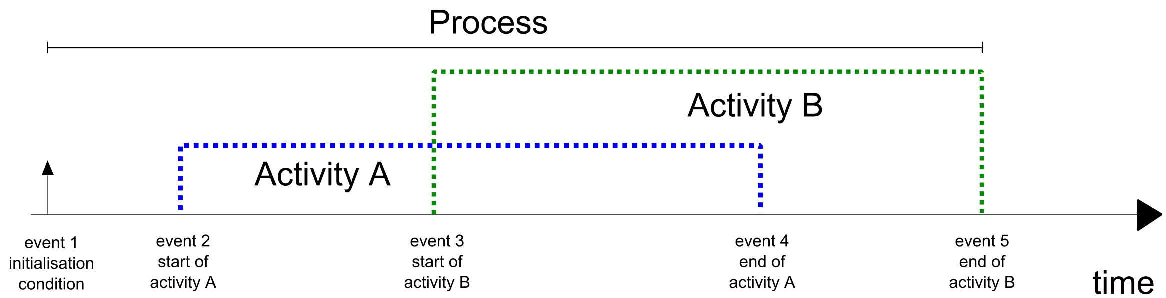

Figure 2: A simple discrete event simulation workflow

Systems Dynamics (SD)

System Dynamics simulation assists the modeler in gaining a better understanding of the balance among the components of a system, and the feedbacks between them (Scholl, 2001) expressed usually in ordinary differential equations (Vincenot et al., 2011). The basic concept of the model is described by a simple stock and flow diagram (Fig. 3). The flow affects the stock based on an equation, and the stock gives feedback on the flow.

The feedback relationships can be either positive or negative. In Figure 3 the relationship between birthrate and population of a species is positive: the more births take place, the larger the population becomes, and the larger the population becomes, the more the births will increase. The feedback relation between deaths and population is negative: the more deaths occur, the smaller the population.

The key advantage of SD is that it captures the feedback and delay processes in order to provide the user with the system behavior over time (Morgan et al., 2011). The user may interactively change the balance of these processes and monitor the effect that this change has to the whole system.

Limitations of SD: SD modeling is better suited to express a closed loop system where the researcher is enabled to fully articulate the relation between two variables. In complex systems, however, a feedback loop is not always so easy to identify, so the adequacy of the simulation may become questionable. SD is best in predicting the evolution of a system in a qualitative way (e.g. growth vs. reduction) rather than making numerical predictions. Moreover, SD models lack the capacity of modifying themselves structurally (Scholl, 2001); hence, no form of adaption can be simulated through this paradigm. Last but not least, SD approaches have no spatial awareness; to the best of our knowledge there has not been an SD implementation incorporating spatial attributes into the model.

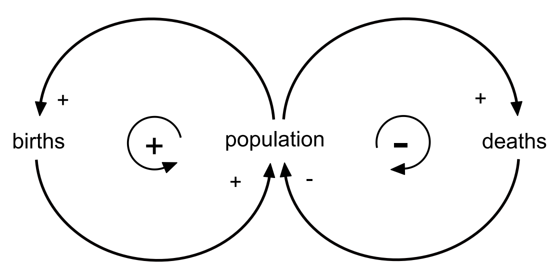

Figure 3: A system dynamic feedback loop example

Hybrid Simulation Approaches

Owing to the individual limitations of the above basic paradigms, a number of researchers have tried to develop hybrid approaches that combine the strengths of multiple simulation paradigms. Hybrid simulation does not seem to be a commonly used term in movement ecology, though it appears to be a rather widely used concept. Simulations in a system dynamics environment often use ABM principles for modeling individual moving objects (Teose et al., 2007); agent based simulations use the focus on events from the DES approach (Dubiel et al., 2005); and the complementary use of SD and DES has also been proposed (Morgan et al., 2011). A considerable number of additional hybrid simulation attempts in other areas can be found in the literature.

Research Gaps

According to Morgan et al. (2011), two key questions should be addressed before developing a simulation: What is the focus of the study? and What is the level of detail required for this simulation? In movement simulation, as Nathan et al. (2008) show, we find fundamental scaling, both in the spatial and temporal dimension. Scales may range from short movement paths that identify a stop in an individual's trajectory; to a longer movement phase that represents a particular movement behavior (e.g. foraging); all the way up to a lifetime trajectory, starting with an individual's birth and ending with its death. Since movement and the behaviors it reveals takes different forms at different spatial and temporal scales, and since over time, environmental conditions and external factors may change, a truly *comprehensive* approach to movement simulation should be capable of modeling movement both at the detailed as well as the global scale, and it should be able to adapt to changes.

As we all know, more is not always better. In the case of movement simulation though, it seems that DES is inherently unable to express the ecological and social dynamics; ABM cannot easily relate to the classic ecological entities; and SD suffers from the lack of spatial expression. Thus, it seems that there is room for exploiting synergies between all three paradigms. The objective of this paper is not to present the perfect all-purpose tool, but rather to propose a consistent approach to exploit synergies among the available simulation paradigms.

To the best of our knowledge, no such *comprehensive, hybrid model* for movement simulation exists. The innovation of the hybrid model is twofold. Firstly, on a technical level, it permits to exploit the advantages of each simulation paradigm and thus be more adaptive than approaches relying on single paradigm. Secondly, in the proposed simulation model the mobile agents' motivation can play a significant role in simulation.

Logical Model for Animal Movement Simulation

The proposed framework aims at translating the established general conceptual framework for movement ecology by Nathan et al. (2008) to a logical model, and extending it. This logical model will be then be expressed with appropriate simulation paradigm(s).

The basic components of the proposed logical model are organized into a static and a dynamic part (Fig. 4). After setting the starting point of the simulation, the *static part* encompasses three main steps, including *condition identification*, identification of *possible movements*, and selection of the *probable movement*. The *dynamic part* updates location, time, and the conditions of the simulation.

Models of time. The flow of the simulation can be event-driven (discrete) or continuous, using different models of time. In the first case the time advances only when the state of a parameter or the position of the moving object changes, whereas in the second case the time advances with a fixed increment from the beginning of the simulation, until the user-defined ending condition is reached. The choice of the model of time that is used may have a crucial effect on the efficiency, the structure of the simulation, as well as the result, and should be adapted to the requirements of the simulation scenario.

Static part.

Initial condition identification. This step gives a starting value to all the active parameters of the simulation model (Fig. 4). First and foremost the user selects the *model of time* (event-driven vs. continuous) and the spatial *movement model* (e.g. random walk, Levy flight, etc.) that the simulation will use. After the selection of the model the user may choose which *external factors* (e.g. temperature, wind speed), and which components of the *internal state* (i.e. instincts, drive, and reflexes) apply in the specific case.

Possible movements. In this step, the system identifies all feasible movements for the individual. Factors that shape the set of possible movements are *motion capacity*, e.g. maximum speed and acceleration, turning angle, possible duration at maximum speed etc. and the *context constraints,* e.g. land for (most) fish, or wide rivers for gibbons. In a way, the possible movements set is based on mechanistic attributes, the physical part of the movement. The capabilities and limitations to the movement of a particular individual or species can be defined by the user, or automatically extracted from a reference dataset, using data-mining algorithms (Torrens et al., 2011).

Probable movement selection. Encompasses the computation of the p-value of all the possible movements, given a user-specified level of confidence α, with the aim of selecting the one with the highest probability. The natural expression of this step is the decision that the individual will likely make on targeting and directing its movement. The calculation of the p-value though, requires bringing to the same scale of measurement all the categorical and continuous variables describing the properties of movement. Such variables are those describing the navigation capacity of an animal, its motivation, as well as additional conspecific characteristics that affect its decision to move. The *navigation capacity* is the individual's capability to perceive its environment; in other words, it requires all the context data that assist an animal to navigate. *Motivation,* on the other hand, is usually goal-oriented and thus a crucial driver of movement activity, associated with a drive such as hunger, thirst, sleep etc., while at the same time remaining closely tied to sensory stimuli. For instance, once food is available to an animal it expresses eating behavior, thus limiting its mobility. Motivation may also be learned, *aka* secondary motivation (Dorman, et al., 1995). Various additional *conspecific variables* might be necessary to better depict the way the animal acts, such as inbreeding behavior, alarm signals, etc.

Dynamic part. The dynamic part is where both simulation time and space (i.e. position) are updated, updating at the same time also the movement conditions (which may have changed since the initial conditions have been set). When the continuous mode of time is selected, then time advances steadily, updating in every time step both the spatial location of the individual and the conditions; e.g. the weather may have changed (external factor), the energy level of the individual may have dropped below a threshold (internal state impacting on the motion capacity), or the individual may reached a lake shore (context constraint). In the discrete time model, the time will be updated every time that an event takes place such as a specific condition change.

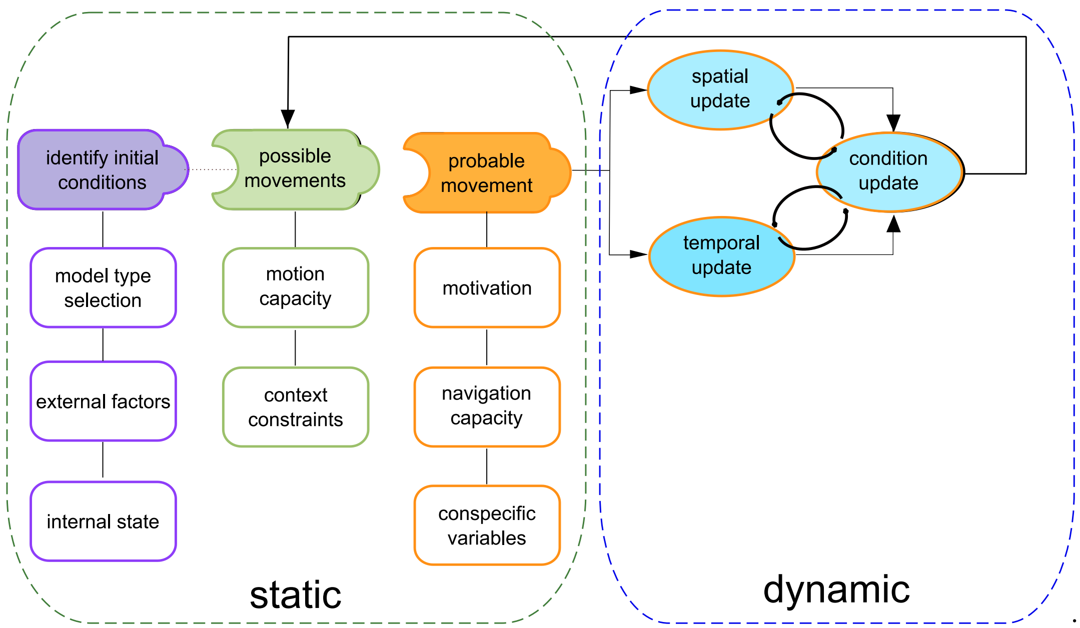

Figure 4: Logical model of movement

Instantiating the Logical Model

In order to illustrate the workflow of the logical model, an instantiation with increasing level of complexity is performed. We use three variables to describe the complexity level:

- *Movement*. Expresses the individual's ability to perform spatial movements. A variety of models, such as random walk, Levy flights, Brownian motion etc. can be used and parameterized as the core movement equation for the individual.

- *Behavior*. Describes the individual's response to a given stimulus. It represents the individual's effort to adapt or adjust to different internal (hunger, fear, tiredness) as well as external conditions (predation, follower-leader behavior, etc.)

- *Context*. Refers to the environment of the individual. Depending on the current type of behavior, the context might be active (i.e. other individuals) or passive (i.e. natural phenomena).

The values of the above variables can be steady, boolean, adaptive, and/or collective. 'Steady' means that only a single state of the variable is available; 'boolean' implies two states; 'adaptive' is when the state can be selected from more than two options based on the current context; and 'collective' is when the selection of the state is taking into consideration the respective selections of other individuals.

Out of the many possible combinations of the above variables and values, four reference cases were defined in order to describe the specific parts of the simulation model. Note that complexity increases in a non-linear fashion over the series of use cases (Table 1).

Table 1: A summary of the reference cases

Case Level	Movement	Behavior	Context
Case 1	Steady	Steady	Single resource
Case 2	Boolean	Boolean	Single resource
Case 3	Adaptive	Adaptive	Single resource – expressed by equation
Case 4	Adaptive & Collective	Adaptive & Collective	Context

Case 1

In the first reference case the individual is represented by a non-intelligent agent, which moves based on a simple random walk, and its behavior is steady, for instance constantly foraging. The context is defined by a single resource, i.e. food.

Making the example more intuitive, a short-sighted, memory less bird is looking for food. It starts with a fixed energy storage that lasts e.g. for 10 random moves of a given time interval. In each time step, it moves to a new location, and checks for resources. If none is present it moves to the next location. Once it finds food resources, it spends one time step not moving, and gains energy for the next 2 steps. Ultimately, if no resources are found, and the energy storage reduces to 0, the bird dies.

The bird's movement and behavior, in this example, is sequential and lacks complexity. No social dynamics of any sort have to be taken into consideration since the bird is not interacting with other birds. Thus, the DES paradigm can offer a simple and sufficient approach for this simulation.

Case 2

In the second case the bird has two different modes to move: either slow (= 1 move per time step) or fast (= 3 moves per time step). The bird here has a rule embedded that controls the change of its behavior. For instance, once the energy level is over a specific level, the bird will move fast instead of making a single move. It has two different options for its behavior, e.g. forage and explore. The available context remains the food. The complexity of this model is higher than in the previous case. However, it is still feasible to approach it using DES, though ABM could also be used. In fact, depending on the scale, the required accuracy and the number of individuals to be simulated, these approaches could be used not only alternatively but also complementarily (Vincenot, et al., 2011). Alternative use would be warranted if the researcher feels more confident in expressing the simulation in one of the two paradigms. Complementary use is advisable in order to optimize the available computational resources, given that ABM comes with higher performance cost, once the simulated individuals start aggregating.

Case 3

In the third case, the bird has an adaptive character. This means that given a specific stimulus, it will act accordingly. For instance, if there is high average concentration of food in six contiguous neighboring cells (assuming a raster representation of spatial context), then it will keep its movement low for the next move – even though it has enough energy stored to move fast.

In this example, the behavior becomes reactive. Reaction is something challenging for the DES paradigm, so an agent-based approach seems more appealing, in spite of the added computing cost. The passive context, on the other hand, may still be expressed as a DES.

Case 4

At this point the simulation model takes a rather complex form, aiming to be more realistic. The moving object expresses both adaptive and collective behavior. In the bird's example, it may forage, chase, follow its mother, flee away from its predator, stay in a nest during night time, etc. At the same time the context also becomes more complex and can include the presence or absence of resources, the risk of predation, atmospheric factors etc. More specifically, the parameters can take the following form:

- Movement: may be described by moving slowly (1 move per time step), fast (3 moves in a straight line), or fleeing from predator (3 moves in a zig zag shape).
- Behavior: the bird might be resting, foraging, migrating etc.
- Context: Multiple choices of food with different levels of energy density, external factors (e.g. temperature, light intensity, humidity etc.), presence of other individuals, and the extent of the home range.

In order to accurately model the behaviors in this case some new parameters have to be defined. Based on the logical model described in the previous section, the bird has a dynamic internal state (energy level, age, physical status), motion capacity, and navigation capacity (Nathan et al., 2008), complemented by its motivation.

From a qualitative point of view, these parameters are not isolated from each other. For instance, once the internal state of the animal records a low energy level in the agent, then the motivation for foraging is much higher than other behaviors. If the animal is threatened (a possible internal state) the agent is likely to behave collectively, and so on. Another relationship concerns the navigation capacity and the age – the older the bird gets the less capacity it possesses. Finally, a more complex relationship concerns resources and mobility– the more resources are available, the less mobility the bird will exhibit.

Having a detailed look at this example it seems that the birds can be adequately simulated with ABM, while DES would suitably assist in simulating certain external factors. Specific rules — low level of energy, fear, etc. — activate the corresponding behavior. The age-dependent evolution of navigation capacity can be simulated in a straightforward way, e.g. using a bell curve equation: until a certain age the bird is having better navigation capacity per year, and after the limit, the capacity levels off or drops.

For modeling the last relationship between the resources and the bird's mobility, let's assume a bird whose mobility reduces as it feeds on a bush of cherry tree. One bird can only eat so much, but if the birds multiply, then it has to be considered that one bush can only support so many birds. In other words, the relationship between a given external factor and its effect on the bird, might be bidirectional. Further extending this thought experiment, if too many birds are present, then suddenly the behavior of the next simulated bird should change back to increased mobility, as the food resource cannot support it. This is a typical form of causality loop that, even though it is computed on the level of each individual, will eventually yield results on a macro level, described by aggregation statistics, population dynamics etc.

Exploiting Synergies: The Hybrid Simulation Model

For the first three reference cases — which, admittedly are significantly simpler than the fourth case — the combination of DES and ABM was capable of supporting these simulation scenarios and maintains an optimized ratio of quality and performance, due to the complementary characteristics of the two paradigms. However, the causal relations among the individuals, can be better approached using SD (Vincenot et al., 2011) due to the inherent nature — flow, stack and feedback loops — of the modeling paradigm. This could be implemented as an autonomous SD sub-model that runs every time step in order to provide thresholds and statistics for the ABM model to run pseudo-concurrently. Overlaying this on top of the proposed logical model of movement simulation (Fig. 5), the ABM and DES models may work in a complementary fashion — when the former becomes too costly, the simulation turns into DES, which means less depth and quality in the calculations of each individual, but much better overall performance — whereas SD may help expressing the interactions taking place among the various elements of the simulation model at a finer grained level.

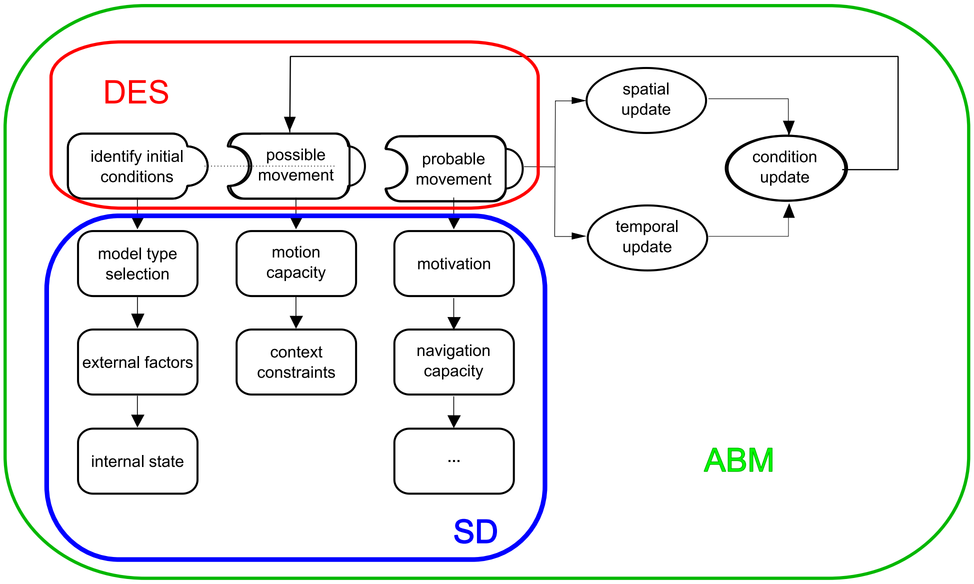

Figure 5: Proposed synergy of the three simulation paradigms: The hybrid simulation model of movement.

Applying the Hybrid Model to Movement Ecology

Of the four reference cases discussed above, the first and second cases are sufficiently constrained so the can be implemented using a single simulation paradigm (DES or ABM). However, chances are that any real-life case would be more complex. The third reference case, then, brings about adaptive (reactive) behavior of the bird, and already suggests to use a combination of paradigms: ABM to implement the reactive behavior of the bird by a set of rules, and DES for the (possibly changing) passive environment.

The fourth case, finally, comes closest to what might be perceived a ‘realistic’ setting for simulation in movement ecology. Given the significant complexity of this reference case, the hybrid simulation model that combines all three paradigms (ABM, DES, SD) has been proposed. This hybrid approach has the advantage of creating sub-models running pseudo-synchronously for each time step, computing the effects of the various simulation components on each other. For instance, the more predators are present, the less the bird feels like foraging; the closer the bird is to starvation, the less it cares for the presence of a predator; the more exposed an environment, the less the motivation to forage. All these are expressed in the form of causality loops that can be incorporated into the model in the form of System Dynamics. As a result of this simulation, the researcher will have the opportunity to see how the model responds to given adjustments of the loops, until the simulated result is comparable to the recorded data. This trial-and-error technique may assist in identifying major properties of the birds’s movement, as well as quantifying the contribution of each one of these to the movement, and thus test ecological theories against simulated data. Furthermore, from the perspective of methods development in GIScience, simulation helps to create realistic test data that may be used to evaluate algorithms for movement data mining and analysis.

Realistic simulation of movement for ecology also involves multiple spatial as well as temporal scales (Nathan et al., 2008). This becomes clearly visible in the fourth reference case. A full-scale simulation of movement involves decisions and behavioral expression at the level of an individual and at the level of entire populations; and it may focus on diurnal variations and span the seasons of the year. Thus, as the fourth reference case shows, it must be possible that the simulated collective behavior incorporates the aggregation of many agents as they interact among each other.

The proposed hybrid simulation model goes far beyond what represents the state of the art in simulation for movement ecology. Typical movement simulators use a single movement model (e.g. CRW, Levy flight, Brownian motion) at a single spatial and temporal scale, and with a single simulation paradigm. However, as mentioned in the review of related work, there is a growing number of hybrid simulation approaches published. In other fields, there is definitely a trend towards hybrid, multipurpose, scalable simulation. Thus, we believe that this trend will also have an effect on simulation in movement ecology. Our hybrid simulation model is hoped to provide the conceptual basis for this.

Conclusions

A hybrid simulation model was proposed that utilizes the combination of the benefits offered separately by agent-based models (ABM), discrete event simulation (DES) and system dynamics (SD). Based on literature we created a logical model that connects and combines the three simulation paradigms in order to better represent the established general conceptual framework for movement ecology by Nathan et al. (2008). Introducing reference cases of an increasing degree of complexity, we pointed out the possible advantages of such a synergetic approach. We also discussed how the reference cases could be mapped to simulation in movement ecology.

There are several innovations that this paper brings about. First, a comprehensive conceptual model for hybrid simulation in movement ecology, relying on the joint use of three different simulation paradigms (ABM, DES, SD), was proposed. Second, this model was used to identify best-fit interactions among these three key simulation paradigms. Third, we highlighted the role of motivation as a main driver of movement. Finally, we have proposed to separate the prediction of the next move into two steps, possible and probable movement, thus allowing to incorporate motivation in the prediction process.

We have started the implementation of the proposed hybrid model at the level of the first two reference cases. However, there are several questions that only an full implementation of all the above paradigms could answer. For instance, no model is theoretically limited to a specific form of modeling capacity or optimization – in other words if the user is highly experienced in simulation programming, he/she should, at least theoretically, be able to create identical applications using any of the paradigms. At the same time the presented combination is not the only one that could be used. Alterations of synergies that can accrue among simulation paradigms are expected to take place, but in general, the simulation model leaves room for adaptation.

The next steps of the ongoing research will focus on moving from the conceptual level to the operational, identifying challenges and pitfalls of the proposed model. Future work follows the logic of the reference cases, starting with simple cases and progressively increasing the level of complexity and realism of the simulation. As we progress, different types of simulation paradigms and techniques will be explored.

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