Co-evolution of Active Sensing and Locomotion Gaits of Simulated Snake-like Robot

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ABSTRACT

We propose an approach of automated co-evolution of the optimal values of attributes of active sensing (orientation, range and timing of activation of sensors) and the control of locomotion gaits of simulated snake-like robot (Snakebot) that result in a fast speed of locomotion in a confined environment. The experimental results illustrate the emergence of a contactless wall-following navigation of fast sidewinding Snakebots. The wall-following is accomplished by means of differential steering, facilitated by the evolutionary defined control sequences incorporating the readings of evolutionary optimized sensors.

Categories and Subject Descriptors

G.1.6–Global Optimization; J.2-Physics

General Terms

Algorithms, design

Keywords

Genetic programming, locomotion, Snakebot, active sensing, navigation

1. INTRODUCTION

Wheelless, limbless snake-like robots feature potential robustness characteristics beyond the capabilities of most wheeled and legged vehicles – ability to traverse challenging terrain that would pose problems for traditional wheeled or legged robots, and insignificant performance degradation when partial damage is inflicted. Some useful features of snake-like robots include smaller size of the cross-sectional areas, stability, ability to operate in difficult terrain, good traction, high redundancy, and complete sealing of the internal mechanisms [3, 6, 24]. Robots with these properties are well applicable in exploration, reconnaissance, medicine and inspection. However, compared to the wheeled and legged vehicles, snake-like robots feature (i) smaller payload, (ii) more difficult control of locomotion gaits and (iii) inferior speed characteristics.

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Focusing on the latter two drawbacks, in this work we intend to address the following challenge: how to automatically develop the control sequences of actuators of realistically simulated snake-like robot (Snakebot), which, incorporating the sensors' information is able to achieve fast speed of locomotion in confined environments.

In principle, the task of designing the controlling code of robots could be formalized and the formal mathematical models incorporated into directly programmable control strategies [2, 16, 18, 20, 23]. However, the eventual models of the Snakebot would feature enormous complexity and such models are not recognized to have a known, analytically obtained exact optimal solution. The complexity of the model stems from the considerable amount of degrees of freedom of the Snakebot, which cannot be treated independently of each other. The locomotion of the Snakebot is viewed as an emergent property at higher level of consideration of a complex nonlinear, hierarchical system, comprising many relatively simply defined entities (morphological segments). In such systems the higher-level properties of the system and the lower-level properties of comprising entities cannot be directly induced from each other [14]. Therefore, while an effective incorporation of sensing information in fast locomotion gaits might emerge from intuitively defined sensing morphology and simple motion patterns of morphological segments, neither the degree of optimality of the developed code nor the way to incrementally improve this code is evident to the human designer [11]. Thus, an automated mechanism for the evaluation of solution and corresponding rules for incremental optimization of the intermediate solution(s) (e.g. based on various models of learning [5, 8] or evolution [7, 12, 21, 22] of species in the Nature) might be needed. However, most of these Nature-inspired approaches consider the relatively simple cases of either (i) two-dimensional locomotion or (ii) an open loop, sensorless control of three dimensional gaits.

Integrating sensor information in the control sequences of the Snakebot adds to the complexity of the design of optimal locomotion gaits. The simplest case of sensing assumes the use of a single sensor (e.g., camera) mounted in the head of the Snakebot. Featuring a single point of failure, such a design compromises the robustness and redundancy which we consider as distinct advantages of the Snakebot over the wheeled and legged robots. Moreover, as suggested in [22], the most efficient locomotion gaits of Snakebot are not necessarily associated with head-first, rectilinear motions, and sidewinding might emerge as a fast and robust locomotion. In such case an eventual fusion of the readings of several sensors, mounted in the segments of the bot would provide the latter with the capability to perceive the features of surrounding environment along its whole body. In addition to the widening the area of the perceived surroundings, multiple sensors offer the potential advantages of robustness to damage of some of them, dependability of the sensors' information and ability to perceive the spatial features of the surrounding environment due to the motion parallax.

However, integrating the signals from many sensors that are rigidly fixed to the segments of the Snakebot faces the challenge of dealing with the uncertain sensors' readings as the latter move synchronously with the coupled segments of the snake. Figure 1 illustrates how the initial, nominal orientation of the axes of the internal coordination systems of the segments of the bot dramatically differs from a sample instant orientation of these axes in the moving bot. A sensor, fixed to the segment of the moving Snakebot would constantly change its spatial orientation, and consequently, might alternatively perceive no signal (when directed upwards), a signal from the ground surface (when directed downwards), from another segment of the snake, or, eventually, from an obstacle.

One of the methods of dealing with moving sensors is to employ a closed loop stabilizers of the sensors' orientation. These stabilizers incorporate gyroscopes as an indicator of the difference between the current and desired orientations of the sensor, an electronic unit which estimates and electrically amplifies the difference, and servos, which, being controlled by the electronic unit move the sensor in the direction that minimizes this difference. Without questioning the technical feasibility of implementing such a system, we view it as too complex, costly, energy consuming and heavy. The latter two drawbacks additionally compromise the already mentioned small payload of Snakebots as (i) more powerful, heavier batteries would be needed and (ii) the components of the stabilizers would add to the overall mass of the bot.

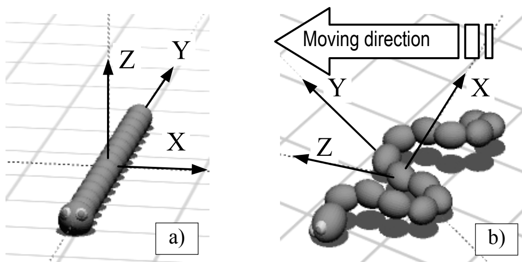

Figure 1. Initial orientation of the axes of the internal coordination systems of the central segment (a) and an instant orientation of the same segment in the moving Snakebot (b).

Another approach of dealing with moving sensors, consonant with the recently emerging active sensing [15], implies an explicit control of the spatial orientation of the sensors in a way that allows the latter (regardless of the position and orientation of the robot) to be oriented towards the relevant objects (e.g., obstacles) of the surrounding environment. We view this approach as unfeasible due to the same payload-related problems as the above mentioned use of gyroscopic stabilizers.

In this study we attempt to explore the possibility to turn the drawbacks of dealing with continuously moving sensors without explicitly controlled spatial orientation into an advantage. Our idea is to fix one sensor per each segment and to let the sensors move synchronously with the segments of the moving Snakebot. Because the sensors in the moving bot move, we might not need servos to explicitly move them towards the desired directions. The moving sensors might periodically, and for a short period of time face the desired directions of sensing. We are interested in whether a properly timed activation of properly placed sensors might be sufficient for the Snakebot to obtain the relevant perception information from the surrounding environment.

The *objective* of our work is to explore the feasibility of automated, evolutionary optimization of (i) the values of the relevant attributes of the sensors (such as the initial orientation, range, and when to activate them) and (ii) the motion patterns of the segments that, incorporating the sensor's readings, yield fast speed of locomotion of a realistically simulated Snakebot situated in a confined environment. From another perspective, our work can be viewed as a simultaneous (co-) evolution of the strongly coupled (i) morphology of active sensing (i.e., the values of the key attributes of continuously moving sensors) and (ii) behavior (i.e., the locomotion gait resulting from the motion patterns of the segments) of Snakebot.

We propose an approach of simultaneous use of genetic algorithms (GA) [4] for optimizing the sensing morphology and genetic programming (GP) [9] for developing the motion patterns of the Snakebot. This implies that both the values of the relevant attributes of the moving sensors and the code, which controls the locomotion of the Snakebot are automatically designed by a computer system via simulated evolution through selection and survival of the fittest in a way similar to the natural evolution of species.

Within this context, the proposed evolutionary design of the simulated, rather than physical Snakebot can be seen as a first step in the sequence of simulated off-line evolution (phylogenetic learning) on the software model, followed by on-line adaptation (ontogenetic learning) of evolved code on a physical robot situated in a real environment [13]. Off-line software simulation facilitates the process of Snakebot's controller design because the verification of the behavior on physical Snakebot is extremely time consuming, costly and often dangerous for the bot and the surrounding environment. Moreover, as in the considered case, it is appropriate to initially model not only the locomotion, but also to co-evolve the most appropriate sensing morphology (i.e., the values of the main attributes of the sensors) of the artifact [13, 17] and only then (if appropriate) to physically implement it as a hardware.

The remainder of this document is organized as follows. Section 2 emphasizes the main features of the evolutionary paradigm proposed for evolution of the Snakebot. Section 3 discusses the experimental results. Section 4 draws a conclusion.

2. EVOLUTIONARY APPROACH FOR CO-EVOLUTION OF MORPHOLOGY OF SENSORS AND LOCOMOTION GAITS

2.1. Representation of Snakebot

Snakebot is simulated as a set of identical spherical morphological segments ("vertebrae"), linked together via universal joints (Figure 2). All joints feature identical (finite) angle limits and each joint has two attached actuators ("muscles"). A single sensor – laser range finder (LRF) with a limited range is attached to the each of the segments in the intersection of the surface of the segment and the plane of both axes of the joint. The functionality of the LRF can be defined by the values of the following set of parameters: (i) orientation, measured as an angle between the longitudinal axis of the sensor and the horizontal axis of the joint, (ii) range of the sensor (in cm), and (iii) the timing of activation, expressed as a threshold value of the turning angle of the horizontal actuator. The reading of LRF is a scalar value which corresponds to the distance between the sensor (if any, within the sensor's range) and an object, measured along the longitudinal axis of the LRF. In the initial, standstill position of Snakebot the rotation axes of the actuators are oriented vertically (vertical actuator) and horizontally (horizontal actuator) and perform rotation of the joint in the horizontal and vertical planes respectively.

Considering the representation of Snakebot, the task of designing the fastest locomotion can be rephrased as developing temporal patterns of desired turning angles of horizontal and vertical actuators of each segment, that result in fastest overall locomotion of Snakebot. The proposed representation of Snakebot as a homogeneous system comprising identical morphological segments is intended to significantly reduce the size of the search space of the GP. Moreover, because the size of the search space does not necessarily increase with the increase of the complexity of Snakebot (i.e. the number of morphological segment), the proposed approach facilitates favorable scalability characteristics of GP.

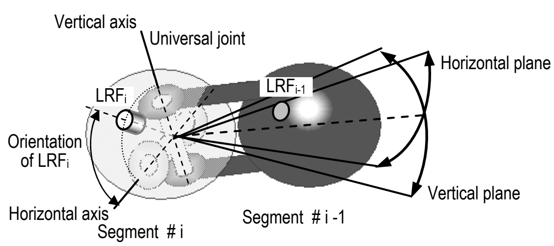

Figure 2. Morphological segments of Snakebot linked via universal joint. Horizontal and vertical actuators attached to the joint perform rotation of the segment `#i-1` in vertical and horizontal planes respectively. A single LRF is attached to each of the segments in the plane of the axes of the universal joint.

2.2 Algorithmic Paradigm

2.2.1 Genetic Representation. Function Set and Terminal Set

In applying GP to evolution of Snakebot, the genotype (Figure 3) is represented as a tripe consisting of (i) a linear chromosome containing the encoded values of the three relevant parameters of LRF, (ii) and two parse trees corresponding to the algebraic expressions of the temporal patterns of the desired turning angles of both the horizontal and vertical actuators, respectively (Figure 3). The Snakebot is genotypically homogeneous in that the same triple is applied for the setup of the LRF and for the control of actuators of all morphological segments. The encoding of the parameters of LRF is elaborated in Figure 3. The same figure also illustrates the function set and the terminal set of the GP, employed to evolve the control sequences of both actuators. Because locomotion gaits, by definition, are periodical, we include the periodic functions `sin` and `cos` in the function set of GP in addition to the basic algebraic functions. Terminal symbols include the variables `time`, `segment_ID`, `ADF`, and `LRF`, and two constants: `Pi`, and a `random constant` within the range [0, 2]. The incorporation of the terminal symbol `segment_ID` (an unique index of morphological segments of Snakebot) allows GP to discover how to *specialize* (by phase, amplitude, frequency etc.) the genetically identical motion patterns of actuators of each of the morphological segments of the Snakebot. The introduction of variable `time` reflects our intention to develop the *temporal* patterns of turning angles of actuators.

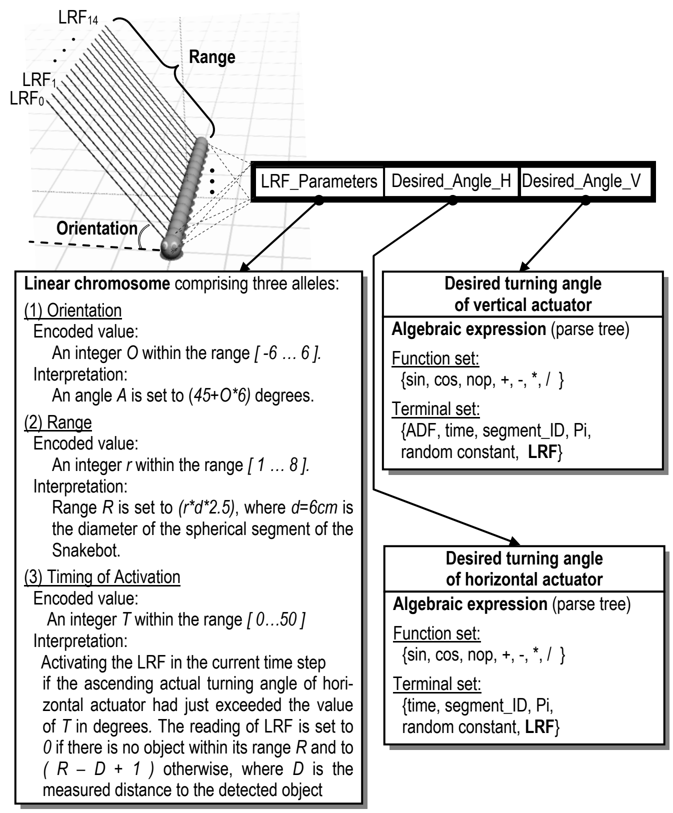

Figure 3. Genotype of the Snakebot, represented as a triple containing the values of parameters of LRF, and two algebraic expressions of the temporal patterns of the desired turning angles of horizontal and vertical actuators, respectively. The genotype of Snakebot is homogeneous in that all segments feature the same triple.

The rationale of employing automatically defined function (ADF) is based on the observation that the evolvability of straightforward, independent encoding of desired turning angles of both horizontal and vertical actuators is poor, although it allows GP to adequately explore the potentially large search space and ultimately, to discover the areas which correspond to fast locomotion gaits in the solution space. We discovered that not only the motion patterns of adjacent segments are correlated, but the motion patterns of horizontal and vertical actuators of each segment in fast locomotion gaits are highly correlated (e.g. by frequency, direction, etc.) too. Moreover, discovering and preserving such correlation by GP is associated with enormous computational effort. ADF, as a way of introducing modularity and reuse of code in GP [10] is employed in our approach to allow GP to explicitly evolve the correlation between motion patterns of horizontal and vertical actuators as shared fragments in algebraic expressions of desired turning angles of both actuators. Moreover, we observed that the best result is obtained by (i) allowing the use of ADF as a terminal symbol in algebraic expression of desired turning angle of vertical actuator only, and (ii) by evaluating the value of ADF by equalizing it to the value of currently evaluated algebraic expression of desired turning angle of horizontal actuator. The main parameters of the GP, used to evolve the temporal patterns of control sequences of actuators, are summarized in Table 1.

Table 1. Main parameters of GP

Category	Value
Genotype	Triple (i) LRF parameters (linear chromosome), (ii) Desired turning angle of horizontal actuator, (parse tree), and (iii) Desired turning angle of vertical actuator (parse tree)
Population size	200 individuals
Selection	Binary tournament, selection ratio: 0.1, reproduction ratio: 0.9
Elitism	Best 4 individuals
Mutation	Random mutation, ratio 0.01
Fitness	Velocity of simulated Snakebot during the trial
Trial interval	500 time steps, each time step accounts for 40ms of “real” time (Total 20s of real time)
Termination criterion	(Generations>40) *or* (no improvement of fitness for 16 generations)

2.2.2 Fitness Evaluation
The fitness function is based on the velocity of Snakebot, estimated from the distance, which the center of the mass of Snakebot travels during the trial. As we shall elaborate later in Section 3, the confined environment that the Snakebot need to clear during the trial is simulated by a bended narrow corridor (Figure 4). The length of the corridor is set to seven lengths of the bot. The velocity of locomotion, needed to reach the end of the corridor for the given time of the trial (20s) corresponds to the fitness value of 150.

2.2.3 Genetic Operations
Selection is a binary tournament. A single point crossover is employed, and the position of the crossover point is randomly (with the same probability) selected between all three components (as shown in Figure 3) of the genotype. Crossover is implemented in a strongly typed way in that only the nodes of the same type from the same components of the triple of genetic representation of parents can be swapped. The mutation randomly alters either a value of allele in the linear chromosome representing the parameters of LRF, or a sub-tree in one of the two parse tress that correspond to the temporal patterns of the control sequences of actuators.

2.2.4 Open Dynamics Engine
We have chosen Open Dynamics Engine (ODE) [19] to provide a realistic simulation of physics in applying actuating forces to the segments of the Snakebot. ODE is a free, industrial quality software library for simulating articulated rigid body dynamics. It is fast, flexible and robust, and it has built-in collision detection. The main ODE-related parameters of the simulated Snakebot are listed in Table 2.

Table 2. ODE-related parameters of Snakebot

Parameter	Value
Number of segments in Snakebot	15
Model of the segments	Sphere
Radius of the segments, cm	3
Overlap between segments, %	25
Length of the Snakebot, cm	66
Volume of the segment, cm^3	113
Density of the segment, g/cm^3	0.9
Mass of the segment, g	100
Type of joint between segments	Universal
Initial alignment of segments in Snakebot	Along Y-axis of the world
Number of actuators per joint	2
Orientation of axes of actuators	Horizontal – along X-axis and Vertical – along Z-axis of the world
Operational mode of actuators	dAMotorEuler
Max torque of actuators, gcm	12000
Max angular velocity of actuators, degrees/s	100
Actuators stops (angular limits), degrees	±55
Coefficient of friction between segments and ground surface	0.5
Coefficient of friction between segments and walls	0.5
Friction model	Pyramid approximation of Coloumb friction model
Sampling interval of simulation, ms	40

3. EXPERIMENTAL RESULTS
This section discusses experimental results verifying the feasibility of co-evolution of the optimal (i) morphology of active sensing and (ii) the control of locomotion gaits (incorporating

sensors information) that yield fast speed of locomotion of the bot situated in a confined environment.

We modeled the confined environment as a narrow slightly bended corridor formed by eight pairs of immobile boxes (“walls”) placed along the X-axis of the world (Figure 4). The bot is initially situated at the left (dead) end of the corridor, with its longitudinal axis perpendicular to the intended direction of moving. The width of the corridor, measured between the first pair of blocks (near the initial position of the bot) is exactly the same as the length of the bot. The width, measured between the remaining seven pairs of blocks is set to 90% of the bot’s length. The length, estimated from the initial position of the bot to the right end of the corridor is seven times the length of the bot. The right hand wall gradually “protrudes” to about 45% of the width of the corridor forming a slight right-hand bend. The average velocity, required to successfully reach the end of the corridor for the allocated time of the trial (500 time steps, or 20s of “real” time) corresponds to the fitness value of 150.

The initial perpendicular orientation of the longitudinal axes of Snakebot and the corridor is influenced by the results of the related work suggesting that the sidewinding (defined as locomotion predominantly perpendicular to the longitudinal axis of the bot) is by far the fastest and most robust locomotion gait for sensorless snake-like artifacts with analogous morphology [22]. Therefore, we expect that in the real-world situations a fast, sidewinding Snakebot would enter the corridor featuring much similar spatial orientation.

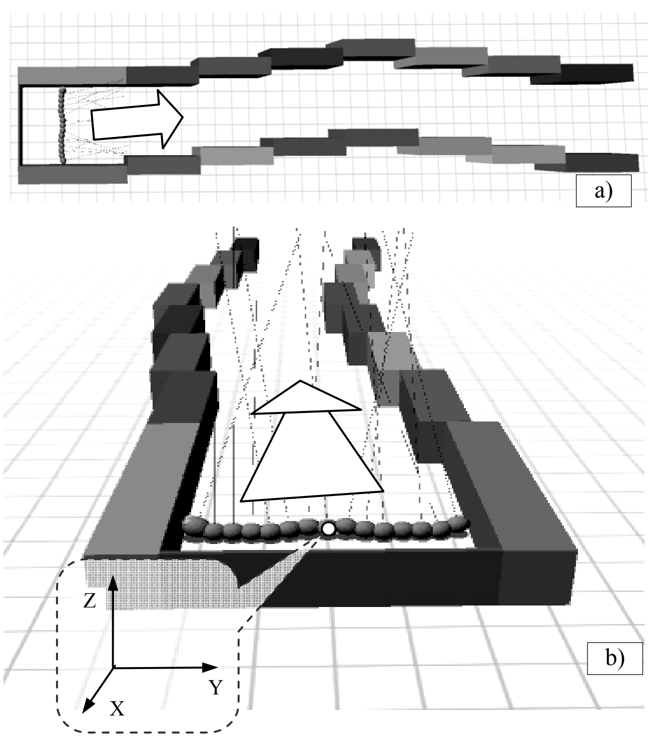

Figure 4. The experimental setup of the scene viewed from above (a) and towards the intended moving direction (indicated by the arrows) (b). The scene comprises a narrow bended corridor and a Snakebot initially positioned near its dead end. The length of the corridor is seven times the length of the bot.

The fitness convergence of 20 independent evolutionary runs is shown in Figure 5. As Figure 5 depicts, in the most (14 out of 20) of the runs the best-of-run Snakebot, evolved for no more than 40 generations, successfully reaches the end of the corridor for the given time of the trial. Investigating these successful runs, we observed the emergence of the following behavioral strategies:

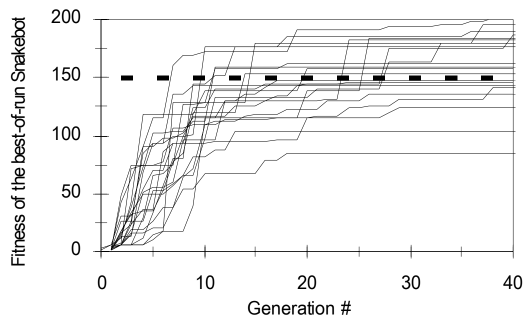

Figure 5. Fitness convergence characteristics of 20 independent evolutionary runs. The dashed horizontal line (fitness = 150) corresponds to the velocity of Snakebot, needed to reach the end of the corridor for the allocated time of the trial (20s).

- “Move fast sidewinding; keep close and occasionally bump from the left side wall of the corridor”. As illustrated in Figures 6a), 6b) and 6c), during the grounded phase of its motion, the head of the sidewinding Snakebot simultaneously slips towards the wall and rotates towards the direction of motion. The head then slips back towards the center of gravity (COG) of the bot (i.e., away from the wall), elevates and moves alongside the wall and towards the moving direction. This characteristic motion pattern implies that the surface of the head collides with the wall during its grounding phase at nearly zero velocity, thus causing no significant degradation of the overall velocity of the bot. It should be noted that such wall-following strategy emerges both as a result of the incorporation of the sensors data in the control of locomotion and a sensorless (open loop) control. In the latter case, the bot inherently turns slightly towards the left walls due to the asymmetry of the amplitudes of the oscillating segments. This strategy is observed in 4 (out of 14) successful runs.
- “Move fast sidewinding; occasionally bump from either wall of the corridor”. As the snapshot of the evolved gait reveals (Figure 6d), this strategy is associated with the emergence of characteristic locomotion trait – a wide winding angle which results in a reduced cross-section of the sidewinding Snakebot. The more compact posture of the sensorless bot in this case minimizes the probability of collision with unperceived obstacles (e.g., walls of the corridor). Moreover, even if the bot occasionally collides with the walls, the impact of the collision on the velocity and orientation of the bot is marginal due to the proximity of the impact point to the COG of the bot. This proximity implies a very low rotational momentum of the forces resulting from the friction between the bot and the wall.

The observed result of the artificial evolution is analogous to the solutions discovered by Nature – it is recognized that natural snakes also change the winding angle of their locomotion gaits in order to adapt themselves to various environmental conditions. We noticed the widening of winding angle of sensorless bot in 6 (out of 14) successful runs.

The abovementioned sensorless strategies emerge as a result of several factors, such as the characteristics of both the Snakebot and the environment, and the design of the fitness function. The latter tries to holistically estimate the performance of the bot (i.e., its velocity) in achieving some low-level objective (i.e. *what* is required to be done) regardless of the way this objective is achieved. The emergence of these strategies illustrates the ability of the evolving Snakebot to learn *how* to accomplish the required objective without being explicitly taught about the means to do so. Such *know-how*, acquired automatically and autonomously, can be viewed as a demonstration of an emergent intelligence [1], in that the domain-specific knowledge of *how* to accomplish the task emerges in the Snakebot solely from the interaction of the problem solver and the fitness function.

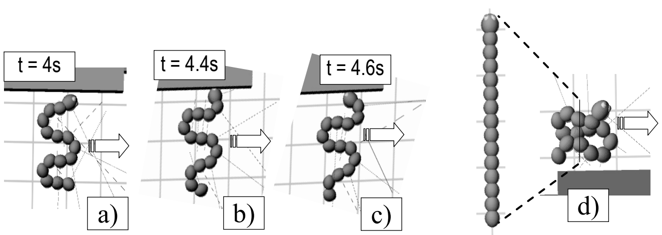

Figure 6. Emergent locomotion traits of the sidewinding Snakebot: bouncing from the left-side wall of the corridor (a, b, and c) and bumping from either left- or right- side walls (or both). In the latter case the detrimental effects of the impact on the velocity is minimized by the reduced cross section of the moving bot (d). In both cases the Snakebot doesn't need to incorporate the readings of its sensors in the control of the locomotion gaits. Arrows indicate the moving direction.

We suppose that by modifying either the fitness function (e.g., explicitly penalizing the bot for colliding with the walls, or for making no use of the sensors' data) or the characteristics of the environment (e.g., including narrower passages and/or sharper turns in the corridor, increasing the coefficient of friction between the bot and the walls, etc.), the sensorless strategies might cease to emerge as winning ones. In our current implementation however, the evolving bot is only implicitly penalized for its eventual collisions with the walls by the naturally occurring degradation of its moving velocity. Therefore, from another viewpoint, the emergence of the discussed strategies can be seen as an illustration of the ability of the bot to learn how to minimize the degree of such degradation.

The best-of-run Snakebots, evolved of the remaining 4 (out of 14) successful runs is of special interest for us, as the emergent behavioral traits demonstrate the incorporation of sensors' information for the steering of the bot in a contactless wall following navigation. The snapshots of such Snakebot in four most principal instants of 5.05s, 10s, 13s and 20s into the trial are shown in Figure 7a). The moving trajectory of the bot is illustrated in Figure 7b).

The evolved sensing morphology in the illustrated sample Snakebot is as follows: the range of LRF is equal to 45 cm (i.e., 75% of the length of the bot), initially oriented at 51 degrees, and activated instantly when the ascending turning angle of horizontal actuator reaches 31 degrees. This sample Snakebot features an overall genotypic complexity of 186 tree nodes. Not uncommon for the cases of automatically evolved solutions, the complexity of the evolved algebraic expressions that define the temporal patterns of actuators is beyond the ability of the authors to comprehend the underlying mechanisms of the incorporation of sensor information into the control sequences of the bot. Rather, we shall elaborate on the sensors readings and the resulting dynamics of the actual turning angles of actuators of three segments of the bot for the four principal instants of 5.05s, 10s, 13s and 20s respectively. The considered three segments are the #1 (next to the head), #7 (the central segment) and #13 (next to the tail).

As figure 7a) illustrates, 5.05s into the trial the bot moves slightly closer to the left-, and away from the right side wall of the corridor, resulting in the corresponding increase of the signal from LRF #7 and decrease of the signal from LRF #13 (Figure 7c). This, in turn inflicts an imbalance between the amplitudes of oscillations (i.e., actual turning angles of the actuators) of the corresponding segments, as the amplitude of the segment #1 is higher than that of segments #7 and #13 (Figure 7e). The effect of this imbalance is a right-hand differential steering of the bot away from the approaching left-side wall of the corridor. Analogous, both right-side and left-side differential steering can be observed at instants corresponding to 10s (right-hand) and 13s (left-hand) respectively. Near the end of the corridor (i.e., 20s into the trial) the peak values of the turning angles of actuators of the considered segments are very similar, resulting in virtually no differential steering of the bot.

Sidewinding locomotion, featuring different winding angle, different wavelength, and different frequency of oscillation emerged in the all four bots that demonstrate a successful, fast wall-following navigation. However, no distinct pattern in the corresponding sensing morphologies of these four bots could be observed. This reinforces our belief that the intricate interplay between the active sensing morphology and the locomotion, rather than some independently considered value of their respective attributes, is responsible for the observed behavioral traits.

4. CONCLUSION

We presented an approach of automated co-evolution of the optimal values of the attributes of active sensing (e.g., orientation, range and timing of activation of sensors) and the control of locomotion gaits of simulated Snakebot resulting in a fast speed of locomotion in a confined environment. The experimental results demonstrate the emergence of a contactless wall-following navigation of a fast sidewinding bot. Such navigation is accomplished by differential steering, facilitated by the evolutionary defined control sequences incorporating the readings of evolutionary optimized sensors.

In our future work we are contemplating an investigation of the robustness of the evolved gaits and the feasibility of their adaptation to changeable environmental conditions (e.g., different friction coefficients, rugged terrain, or sharper turns) and Snakebot's capabilities (e.g., partial damage inflicted to some of the actuators and sensors).

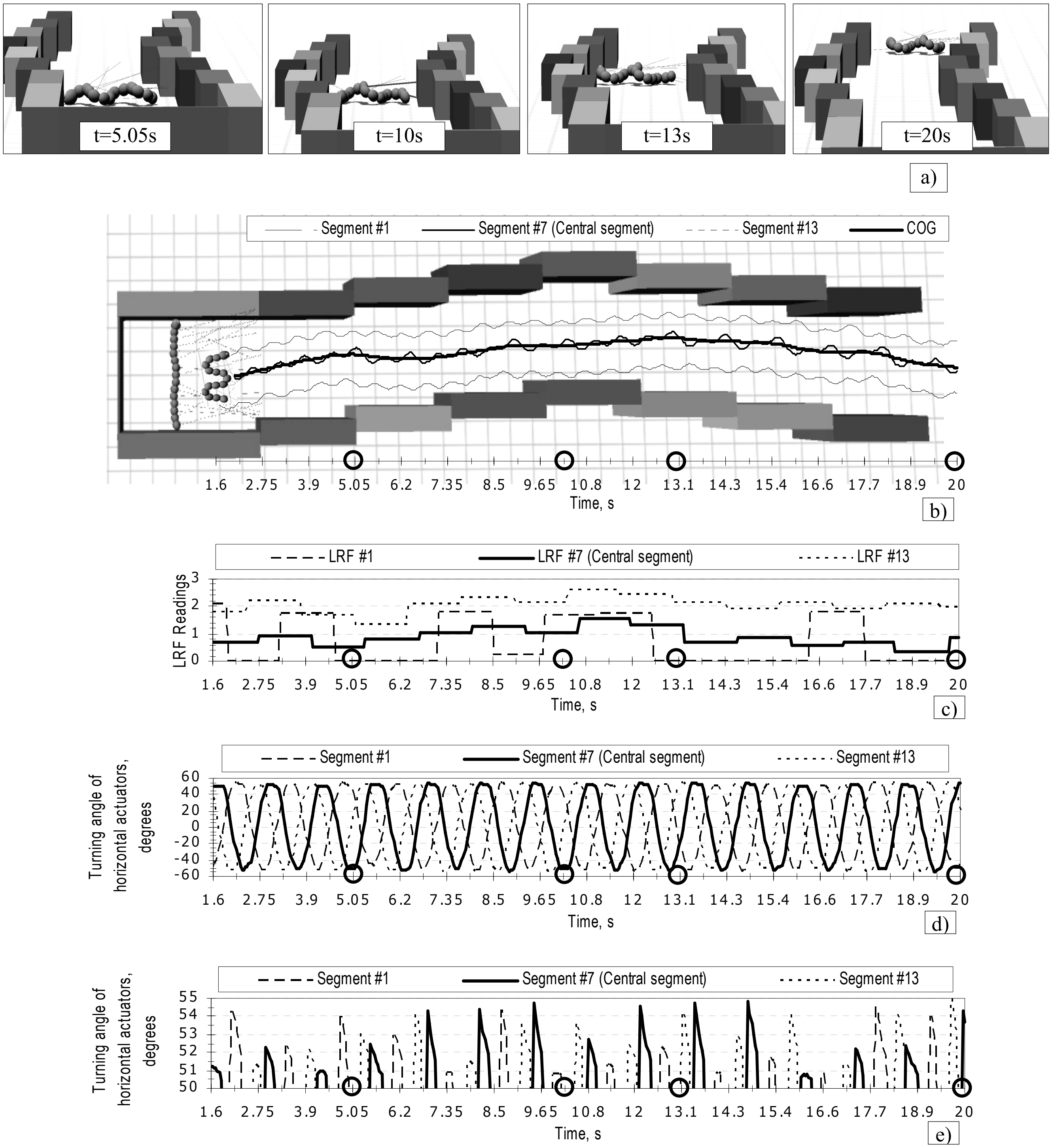

Figure 7. The snapshots (a), moving trajectory (b), readings of LRF attached to segments #1 (next to the head of the Snakebot), #7 (the central segment) and #13 (next to the tail) (c), oscillating patterns (d) and peak values (e) of actual turning angle of horizontal actuators of the same three segments of the sample best-of-run Snakebot. The turning angle of vertical actuator (not shown) is well coordinated with the horizontal one, and features analogous patterns. The four snapshots shown in (a) corresponds to four principal instants of the trial. These instants are indicated by corresponding circles on the abscises of (b), (c), (d) and (e).

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