Design of a Genetic-Fuzzy System for Planning Crab Gaits of a Six-legged Robot

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This paper describes a genetic-fuzzy system in which a genetic algorithm (GA) is used to improve the performance of a fuzzy logic controller (FLC). The proposed algorithm is tested on a number of gait-generation problems of a hexapod for crossing a ditch while moving on flat terrain along a straight line path with minimum number of legs on the ground and with maximum average *kinematic margin* of the ground-legs. Moreover, the hexapod will have to maintain its static stability while crossing the ditch. The movement of each leg of the hexapod is controlled by a separate fuzzy logic controller and a GA is used to find a set of good rules for each FLC from the author-defined large rule base. The optimized FLCs are found to perform better than the author-designed FLCs. Although optimization is performed off-line, the hexapod can use these FLCs to navigate in real-world on-line scenarios. As an FLC is less expensive computationally, the computational complexity of the proposed algorithm will be less than that of the traditional methods of gait generation.

Keywords: Genetic-fuzzy system, crab gait, hexapod, static stability, kinematic margin.

1. Introduction

Genetic algorithms (GAs) are population-based search and optimization techniques which mimic the mechanics of natural selection and natural genetics (Goldberg 1989). On the other hand, fuzzy logic controller (FLC) - a successful application of fuzzy set theory - is a potential tool for handling imprecision and uncertainty (Kosko 1994). To get advantages of both the techniques, a GA is merged with the fuzzy logic technique. Research is going on in both the directions - in one approach, an FLC is used to improve the performance of a GA (Herrera et al. 1994), whereas in the other implementation a GA is used to design an optimized FLC (Karr 1991). Our present work is also based on the second approach. Evolutionary techniques have been used by several investigators for fuzzy rule generation. In this connection, the work of Ishibuchi et al. (1997), Bonarini (1996, 1997), Glorennce (1996), Cordon and Herrera (1996), Cupal and Wilamowski (1994) are worth mentioning. In our genetic-fuzzy system, a GA tries to find a set of good rules from the author-defined large rule base so as to optimize the performance of an FLC.

A legged robot is preferred to a wheeled robot particularly for the locomotion on rough terrain, although, the locomotion mechanism of the former is relatively complicated. A *gait* is a sequence of leg motions coordinated with a sequence of body motions for the purpose of transporting the body of the legged robot from one place to another. A gait is periodic if similar states of the same leg during successive strokes occur at the same interval for all legs, that interval being the *cycle time*. Otherwise, it is a non-periodic gait. Periodic gaits are suitable for smooth terrain. Song and Waldron (1989) provide an extensive survey on different methods of periodic gait generation. On the other hand, non-periodic gaits are suitable for rough terrain and for varying terrain conditions. Both graphical as well as analytical methods have been tried by several researchers for solving non-periodic gait generation problems. In this connection, the work of Kumar and Waldron (1989), Pal and Jayarajan (1991), Jimenez and Santos (1997) are significant. The main drawback of these methods is their computational complexity. Moreover, since no effort is spent on optimization, the generated gaits are far from being optimal. Thus, there is still a need for the development of a computationally tractable algorithm. Some heuristic approaches have also been tried by several investigators to reduce the computational complexity. Beer et al. (1992) solved the gait generation problem using neural network (NN) but in their approach, there is a chance of the solution for getting trapped into local minima. As training is required in neural network, its computational complexity is more compared to a fuzzy logic controller. In this work, the problem of crab gait generation of a hexapod while crossing a ditch has been solved using a genetic-fuzzy system.

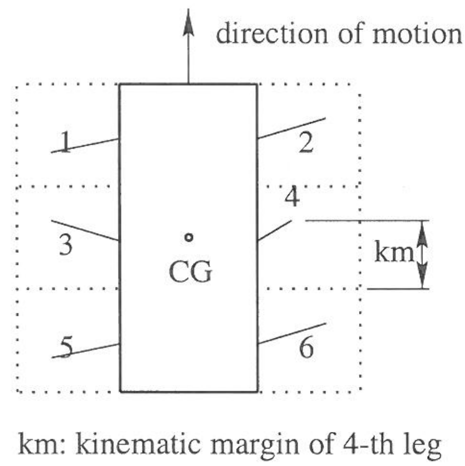

Fig. 1. A schematic diagram of a six-legged robot.

2. A Few Definitions

1. *Transfer phase*: The transfer phase of a leg is the period during which the foot is in the air.
2. *Support phase*: The support phase of a leg is the period during which the leg is on the ground.
3. *Stroke*: It is defined as the distance through which the foot is translated relative to the body during the support phase.
4. *Stability margin*: It is the distance of the vertical projection of center of gravity (CG) of the body to the boundaries of the support pattern in the horizontal plane.
5. *Kinematic margin*: It is defined as the distance from the current foothold of leg i to an intersection with the leg i reachable area in the opposite direction of body motion (refer to Figure 1).
6. *Crab axis*: It is the axis which goes through the body center and is aligned with the direction of body motion.
7. *Crab angle*: It is the angle from the longitudinal axis to the direction of motion, which has the positive measure in the counterclockwise direction.

3. Problem Formulation

A six-legged robot will have to cross a ditch while moving on a flat terrain along a straight-line path (only translation). The hexapod will cross the ditch with minimum number of ground-legs and with maximum average kinematic margin of the ground-legs. Moreover, its stability margin should always be positive to ensure static stability. It is to be noted that as the number of ground-legs increases, the probability of a deadlock increases, too. It is also interesting to note that the average kinematic margin of the ground-legs will indicate the potential progress of the vehicle. Thus, it can be treated as a constrained optimization problem.

The terrain is discretized into cells and the center of each cell is considered as a candidate foothold. The contact of the feet with the terrain can be modeled as point contacts and there is no slipping between the foot and the ground. It is also assumed that all the mass of the legs is lumped into the body and the center of gravity is located at the centroid of the body.

Figure 1 shows a hexapod with the reachable area for each leg as indicated by a dotted square. We consider two reference frames, namely world coordinate frame $\{W\}$ and body coordinate frame $\{B\}$, as shown in Figure 2 for the purpose of analysis. The origin of the body coordinate frame is fixed at the center of gravity of the hexapod.

Here, ${}^{W}_{B}T$ represents the transformation vector from $\{W\}$ to $\{B\}$ and ${}^{B}l_i$ indicates the position of i-th leg with respect to the body coordinate frame $\{B\}$. The position of i-th leg with respect to the world coordinate frame $\{W\}$ is represented by ${}^{W}l_i$. The position of a foot in the body coordinate frame is related to the position

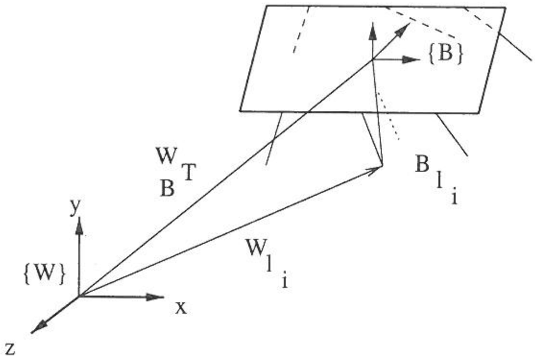

Fig. 2. A schematic showing world frame and body frame.

in the world coordinate frame as given by the expression:

$$^{B}l_i = ^{W}l_i - ^{W}_{B}T \tag{1}$$

The term $^{W}_{B}T$ can also be expressed as ^{W}G, where $^{B}l_i$, $^{W}l_i$ and ^{W}G are expressed as follows: $^{B}l_i = (^{B}X_i, ^{B}Y_i)^T$, $^{W}l_i = (^{W}X_i, ^{W}Y_i)^T$, $^{W}G = (^{W}G_X, ^{W}G_Y)^T$.

The stability margin (as defined earlier) can be calculated using the expression:

$$s_{ij} = \frac{U}{V}, \tag{2}$$

where

$$U = {}^{W}X_i \times {}^{W}Y_j - {}^{W}Y_i \times {}^{W}X_j + {}^{W}G_Y \times ({}^{W}X_j - {}^{W}X_i) + {}^{W}G_X \times ({}^{W}Y_i - {}^{W}Y_j),$$

$$V = \left[({}^{W}Y_i - {}^{W}Y_j) \times ({}^{W}Y_i - {}^{W}Y_j) + ({}^{W}X_i - {}^{W}X_j) \times ({}^{W}X_i - {}^{W}X_j)\right]^{\frac{1}{2}}.$$

Here, i and j are the positions of the feet of two supporting legs of a hexapod calculated in the anti-clockwise direction. Thus, s_{ij} will have a positive value only when the CG of the body lies inside the support polygon which is a necessity for maintaining static stability of the vehicle.

Here, the total distance to be covered by the hexapod is divided into $Q(=9$, chosen here) equal parts usually known as *motion segments*. Decisions regarding lifting and placing of legs are taken at the end of each motion segment.

The problem can be stated mathematically as follows:

Maximize $\quad z = w_1 \times (6 \times Q - C) + w_2 \times K \quad (3)$

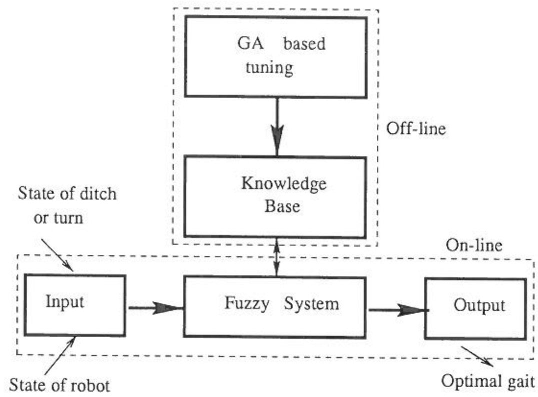

Fig. 3. A genetic-fuzzy system.

subject to the conditions that the hexapod's leg does not fall on the forbidden zone and the stability margin, is restricted as

$$s > 0$$

where C is total number of ground-legs in Q motion segments, K indicates the average kinematic margin of the ground-legs, s (same as s_{ij}) indicates the value of stability margin, w_1 and w_2 are the weighting factors.

4. Proposed Algorithm

In our genetic-fuzzy system, we attempt to find an optimized FLC using a GA. The performance of an FLC depends on its rule base and membership function distributions. It is seen that optimizing rule base is a rough tuning process, whereas optimizing membership function distribution is a fine tuning process (Deb et al., 1998). Thus, in this study, we optimize the rule base of an FLC only. Figure 3 shows a genetic-fuzzy system. There are actually six FLCs working in parallel and the motion of each leg is controlled by a separate FLC. We find a hypothetical intersection point, e (refer to Figure 4) of the line joining the two extreme points of the ditch and the crab axis. There are two inputs (*distance* and *relative angle*) and one output (*stroke*) of the fuzzy logic controller.

The *distance* is the distance of the foot of a particular ground-leg from the intersection point e. The *relative angle* is the angle between the line joining the two extreme points of the ditch and the crab axis. The term *stroke* has been defined earlier. The proposed algorithm

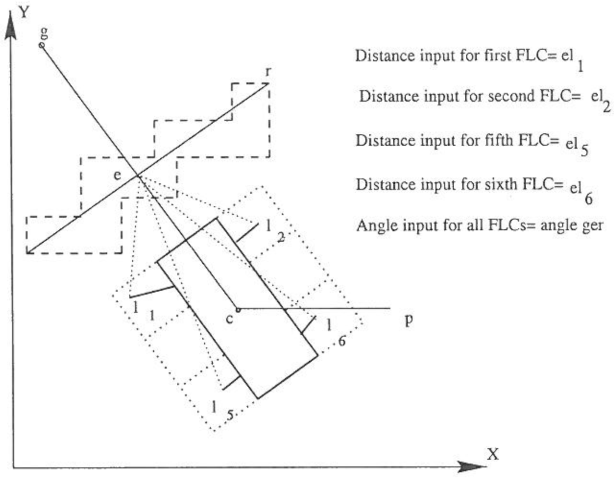

Fig. 4. A schematic showing inputs of an FLC.

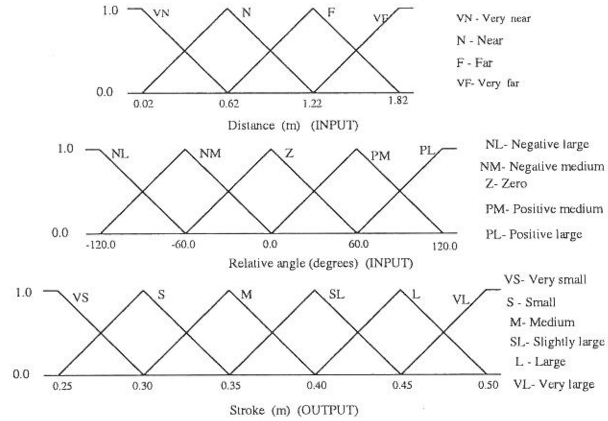

Fig. 5. Author-defined membership function distributions for input and output.

is based on the *stroke control strategy*. Here, we have considered four and five different values for *distance* and *relative angle*, respectively. Moreover, the output (*stroke*) has six different values. The membership function distributions for input and output used in this study (author-defined) are shown in Figure 5. For the sake of simplicity, we consider the shape of the membership function distributions to be triangular. For each FLC, 20 rules are considered. Thus, we consider 120 rules for all six FLCs. The author-defined rule base for an FLC is shown in Table 1 and it is the same for all six FLCs. Thus, a typical fuzzy rule will look as follows:

If *distance* is *VN* and *relative angle* is *NM*,
then *stroke* is *SL*.

The following steps are considered for designing the crab gait of a hexapod while crossing a ditch:

1. We determine the position of CG of the body at each motion-segment. It is to be mentioned that the movement of the body is the same with that of the CG, for a straight-line motion.
2. The stroke for each ground-leg is determined using a fuzzy logic controller.
3. Decision regarding the leg to be lifted to air, is taken based on the kinematic margin calculation at the immediately next and predicted support pattern (the support pattern just after transfer phase). If the kinematic margin of a particular leg is either zero or negative in the next support pattern, the leg is lifted to the air.
4. At the beginning of a particular motion-segment, if the kinematic margin of a leg is either zero or negative, it is selected as a transfer-leg.
5. For static stability of the body, the CG should always lie inside the support pattern. If the stability is not maintained, decision regarding foot placement is made. The leg on the air and with positive kinematic margin is selected for placement on the ground, if required at all. There are some predefined candidate footholds for the placement of a leg on the ground.
6. If the stability (static) is maintained, the vehicle is allowed to move.

It is to be noted that the same support pattern may continue only if the vehicle continues to remain stable and the supporting legs remain within their reachable area. The step-worthiness of the terrain is also checked to ensure that the vehicle does not fall on the ditch.

Since the objective is to maximize z (refer to equation 3), we use a binary coded GA to find a string which corresponds to the maximum fitness value. Each member of the population is represented by a binary string of length 120. The fitness is calculated for each member and it is modified in the subsequent generation using different GA-operators, namely reproduction, crossover and mutation (Goldberg 1989). It is important to mention that the actual optimization is done off-line. Once the optimal rule base is obtained, the hexapod can use it to navigate in real-world on-line scenarios.

5. Results

We use population size of 100, crossover probability of 0.9, mutation probability of 0.01 and run GA for 50 generations. To show the effectiveness of the proposed algorithm, we present simulation results of the gait generation problem of a hexapod crossing a ditch. We studied two different approaches here.

Approach 1: Author-defined fuzzy-logic controller. In this approach, a fixed set of 120 rules and author-defined membership functions (Figure 5) are used. Table 1 shows a set of 20 author-defined rules used in one FLC and the same rule base is used

relative angle

distance	NL	NM	Z	PM	PL
VN	M	SL	L	SL	M
N	S	SL	L	SL	S
F	S	M	L	M	S
VF	S	S	SL	S	S

Table 1. Author-defined rule base for each FLC

relative angle

distance	NL	NM	Z	PM	PL
VN			L		M
N	S	SL	L		
F		M			
VF	S			S	S

Table 2. Optimized rule base for the first FLC (having nine rules only) obtained using Approach 2.

relative angle

distance	NL	NM	Z	PM	PL
VN	M			SL	M
N	S	SL	L	SL	S
F				M	S
VF	S		SL		

Table 3. Optimized rule base for the second FLC (having twelve rules only) obtained using Approach 2.

relative angle

distance	NL	NM	Z	PM	PL
VN	M		L	SL	M
N				SL	S
F		M	L	M	S
VF		S	SL		

Table 4. Optimized rule base for the third FLC (having twelve rules only) obtained using Approach 2.

relative angle

distance	NL	NM	Z	PM	PL
VN		SL			M
N		SL			S
F	S		L	M	
VF			SL	S	S

Table 5. Optimized rule base for the fourth FLC (having ten rules only) obtained using Approach 2.

relative angle

distance	NL	NM	Z	PM	PL
VN		SL		SL	M
N	S	SL	L		
F		M	L	M	
VF		S	SL	S	

Table 6. Optimized rule base for the fifth FLC (having twelve rules only) obtained using Approach 2.

relative angle

distance	NL	NM	Z	PM	PL
VN	M			SL	M
N					
F	S	M			S
VF	S		SL		

Table 7. Optimized rule base for the sixth FLC (having eight rules only) obtained using Approach 2.

Scenario	Approach 1		Approach 2	
	C	K	C	K
1	36	1.36111	35	1.48281
2	37	1.37981	36	1.49865
3	37	1.43173	37	1.54208
4	37	1.37981	36	1.49865
5	38	1.39038	37	1.50629
6	36	1.36111	35	1.48281
7	-	-	37	1.43542

Table 8. Number of ground-legs, C and average kinematic margin of ground-legs, K obtained by two approaches.

in all six FLCs. Thus, there is a fixed set of 120 rules. No optimization method is used to find the optimal rule base or to find the optimal membership function distributions.

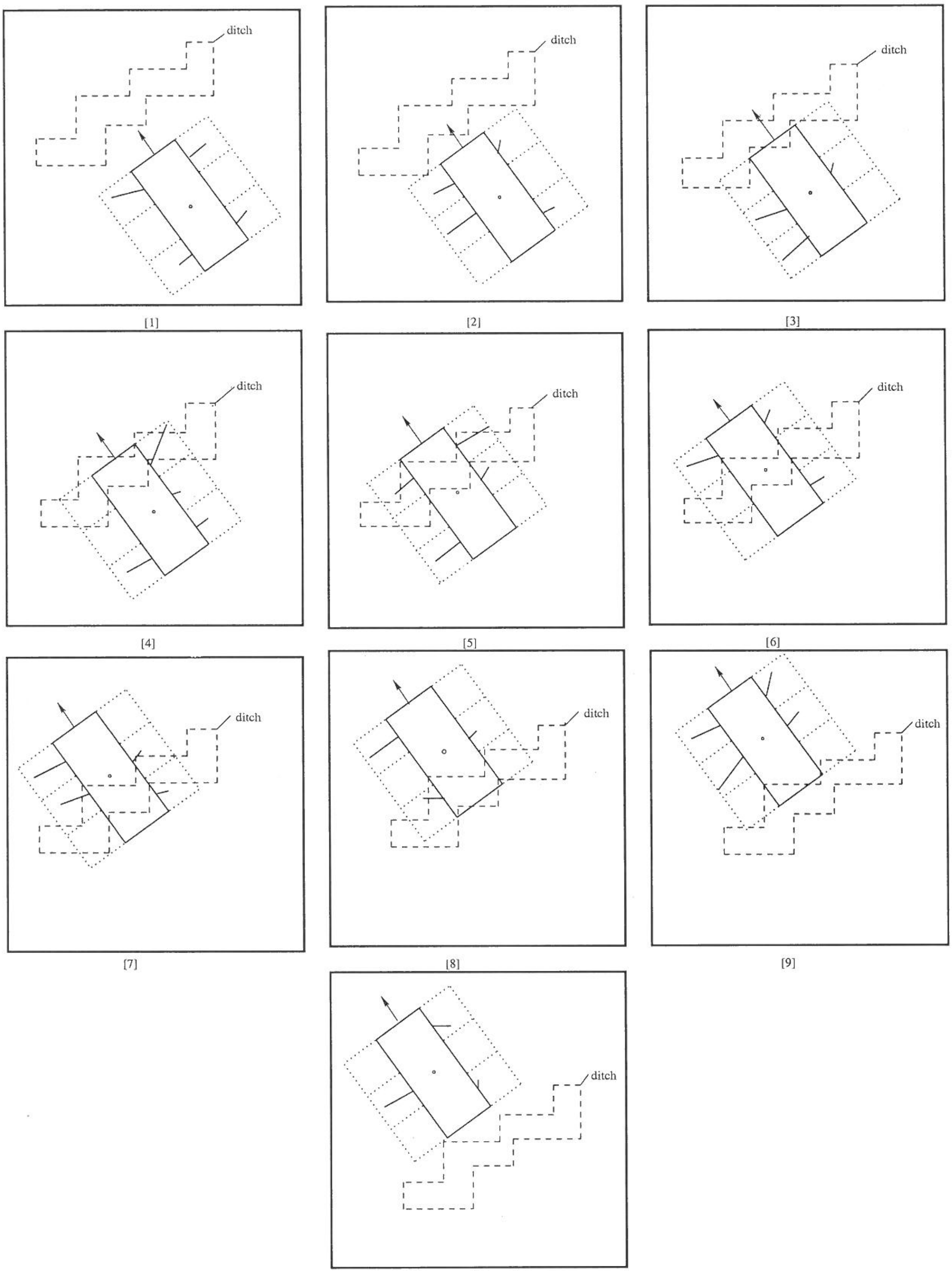

Fig. 6. Generated gaits obtained using Approach 2 for test scenario 4 (Table 8).

Approach 2: Optimizing rule base alone. In this study, we optimize the rule base keeping the membership function distributions same as shown in Figure 5. The maximum number of possible rules is 120. Here, a binary coded GA with 120-bit string is used in which 1 and 0 indicate presence and absence of rules, respectively. Thus,

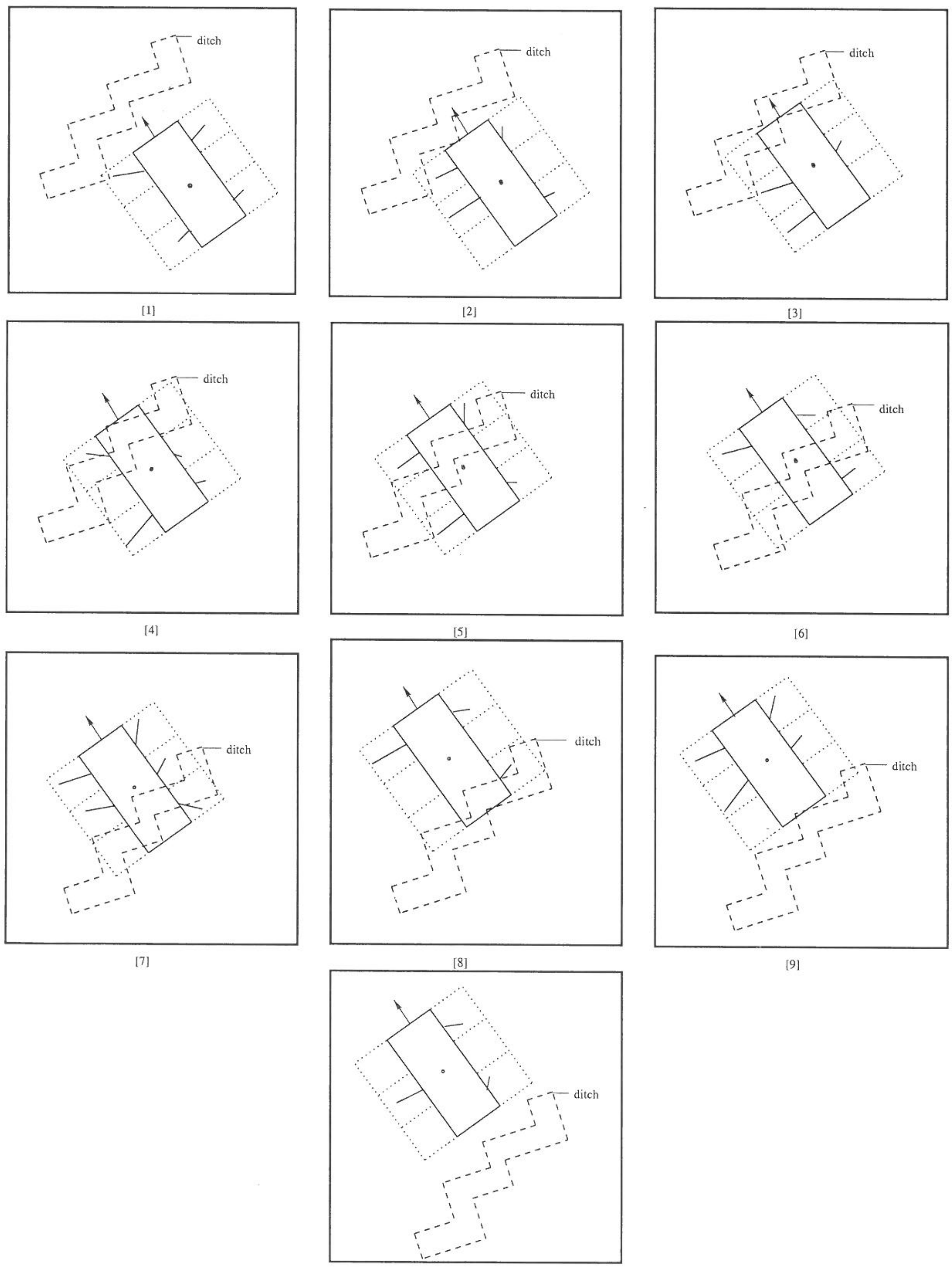

Fig. 7. Generated gaits obtained using Approach 2 for test scenario 7 (Table 8).

a GA will find for which (and how many) rules from these 120 rules will result in a situation in which a hexapod will cross a ditch in the optimal sense. We consider $H=10$ different scenarios and find the average z (refer to equation 3) which is taken as actual objective function value for the maximization problem. In this study, the weighting factors w_1 and w_2 are set to 1.0 and 5.0, respectively.

The gait generation problem is solved using both approaches mentioned above. The optimized rule base obtained through approach 2 for the first through sixth FLCs are shown in Tables 2 through 7, respectively. The minimum number of ground-legs and the maximum average kinematic margin are presented for the two approaches in Table 8. In this table, three scenarios (out of 10) used during the optimization process are shown in the first three rows. The subsequent four rows show four different and new scenarios which were not used during the optimization process. It is to be noted that the *relative angle* varies from one scenario to another. In scenario 7 (Table 8), it is seen that the author-defined FLCs have failed to generate stable gaits for the hexapod, whereas the GA-designed FLCs have successfully generated the stable gaits while crossing a ditch. In all cases, the GA-designed FLCs are found to perform better than the author-defined FLCs. The generated gaits obtained using Approach 2 for the test scenarios 4 and 7 (Table 8) are shown in Figures 6 and 7, respectively (the ditch is shown by dashed lines). It is interesting to note that the same rule base generates two different gaits for negotiating two different ditches, although they started with similar gaits.

6. Conclusions

From this study, conclusions have been drawn as follows:

1. The proposed algorithm is able to solve the gait generation problem of a hexapod effectively. Simulation results show that a GA-designed FLC has performed better than an author-defined FLC. This is because an author-defined knowledge base for the FLC may not be optimum.
2. As optimization is done off-line, the proposed algorithm is suitable for on-line implementation. As an FLC is less expensive computationally, our proposed algorithm will be computationally cheaper compared to the traditional methods of gait generation.
3. Rule-base optimization involves the problem of dealing with discrete variables and GA is a powerful tool for solving this type of problems.

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