PLIF: PIEZO LIGHT INTELLIGENT FLEA
NEW MICRO-ROBOTS CONTROLLED BY SELF-LEARNING TECHNIQUES

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ABSTRACT

A new type of micro walking robots named PLIF (Piezo Light Intelligent Flea) is introduced. These robots, that walk by using piezoceramic legs, are very small in size, but, at the same time, fast and agile. Three different types of PLIF have been designed and built and several dynamic measures have been performed. Moreover a self-learning technique has been implemented and tested in order to increase the autonomy of these systems.

1. INTRODUCTION

Microrobotics researches require to operate on autonomous devices with simple design and limited costs and energy consumption, even if this fact limits the possible tasks of each single robot.

In the last few years the interest in micro mechatronic systems is increasing and several different kind of microrobots have been designed [1], [2],[3]. Applications of these robots can be found in micromachinig, inspection of small environments, micro-surgery, medicine [4], study of co-operating systems etc.

In microrobotics particular attention should be paid in the selection of actuators, keeping in mind power consumption and size and weight of the components [5]. Among the different kind of actuators that have been adopted for microrobots we can mention pneumatic [6], electrostatic [7], shape-memory [8] and piezoelectric [9].

This paper wishes to increase the knowledge in this robotic area by choosing an innovating design for the locomotion of the robots. Our aim was to build walking microrobots, named PLIF (Piezo Light Intelligent Flea), that could be fast, agile small, light, cheap and autonomous in order to study experimentally self-learning strategies and collective behavior of robots. For this reason we have chosen piezoelectric actuators that are robust, strong, low-consuming and have a good displacement resolution [10],[11].

2. PIEZOELECTRIC MATERIALS

Piezoelectric materials are characterized by their ability to produce charges when they are stressed and viceversa. This means they are even able to generate a force if a voltage difference exists between two faces of the piezoelectric bar [10],[11]. In particular we used piezoceramic bimorph elements that consists of two thin piezoelectric layers, 15 mm long, separated by a common electrode. When voltage difference is applied between the two terminals, one piezoelectric layer stretches while the other shortens so that the entire structure bends toward the shorter side, as is shown in Fig.1. In our operative conditions the maximum displacement that can be obtained is then *Δx=36μm*.

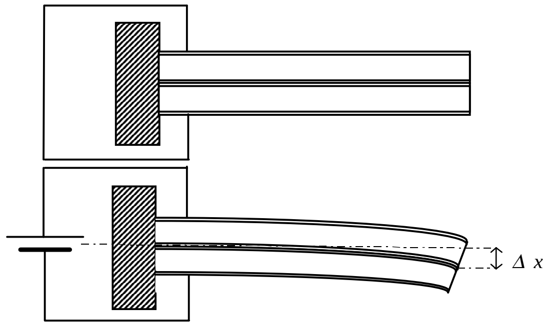


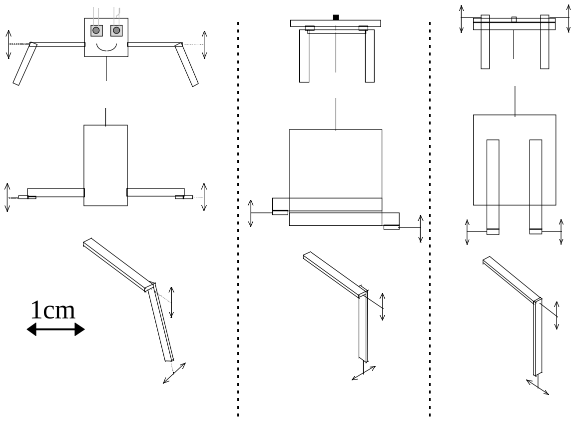
Fig. 1. Piezoelectric effect on bimorph piezoceramic layers.

3. STRUCTURE DESIGN

3.1 Mechanical part

In our micro-robots the piezoceramic bimorphs have been adopted not only as actuators, but also as a part of each micro leg. In particular in order to build a walking micro-robot the simplest steady configuration has been chosen: two active legs moving and one passive as support. Each leg is composed by two parts realized by using two bimorph piezoceramic actuators each one 15mm long: the *femur*, that acts for the vertical movements of the leg, and the *tibia* that acts for the horizontal movements.

Three different solutions of PLIF, schematically shown in Fig. 2, have been proposed. In the first prototype (PLIF I) the moving legs have been stuck externally to the body, the femur and the tibia of each leg make an angle of about 130 degrees, which allows a more uniform grip on the ground. However the difficulties in assembling the pieces bring to an asymmetric structure that is unsuitable for a correct walk.



PLIF I **PLIF II** **PLIF III**

Fig. 2. The structure of the three different PLIF (front view, upper view and structure of a single leg).

The second prototype (PLIF II, Fig. 3) is smaller ($4cm^2$ of total surface occupied), having the legs fixed under the robot body; moreover the two pieces are orthogonally linked to prevent assembling problems.

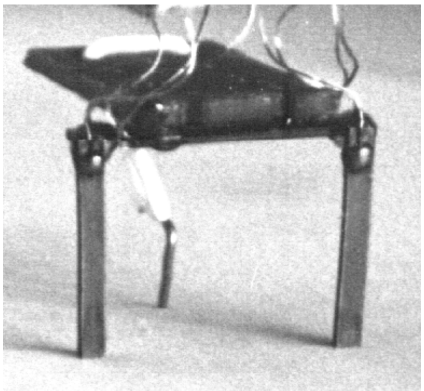


Fig.3. PLIF II

Finally we worked out a structure (PLIF III, Fig. 4) in which the robot leg articulation imitates the human one instead of the spider one . Adopting this last solution the best results in both size and symmetry is reached. This gave us the best performances in motion too. Obviously we should assemble the legs with very accurate instruments to simplify the set up and the movement modeling and identification.

Thanks to the possible movements of the piezoelectric pieces at high frequency and taking advantage of the resonant behavior, a speed up to 18 cm/s has been achieved. Moreover the continuous vibrations of the legs avoid the consequences of static friction that are deleterious during micro-positioning.

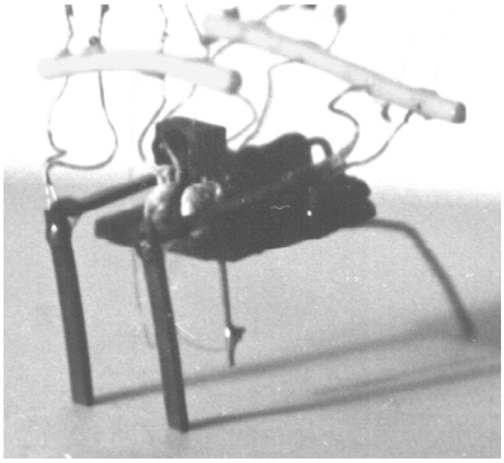


Fig. 4. PLIF III

3.2 Control strategy and hardware electronic

During the human being walk the femur is lifted while tibia is advancing. This is an inferior limit for the frequency of the steps, in fact if x is the level above ground of the tibia and T is the oscillation period of the leg, it should result approximately

$$gT^2<2x \qquad (2)$$

In our case since $x\approx40\mu m$, $g\approx10ms^{-2}$, this means as results that f > 360Hz. It has been experimentally verified that under a frequency of about 400Hz the movements of the robot slow down and they become tripping until the robot stops (at about 250 Hz). The steps frequency has also an upper limit caused by the rising time of the collector voltage of control transistors adopted to drive the bimorphs. This is due to a low-pass filter which consists of the capacity of the piezoelectric pieces and the collector resistance of the driving circuit. In our case the upper limit was $f=2.4kHz$.

Even if the actual implementation of the control board is separate from the robot that is connected with some small wires, the final project impose autonomous, intelligent and cheap microrobots. For these reasons hardware and software solutions that could be simply implemented on a custom chip onboard have been considered [7] [12].

For example the 100V DC power supply, needed to move the piezoceramic actuators, has been realized by using a diode-capacitor voltage multiplier that permits to use a solar cell or a little accumulator as power source, taking into account the small power consumption achieved by increasing RC but lowering the upper limit of steps frequency. The other electronic parts, including the control circuitry, use very simple digital and analog electronic components that could be easily integrated.

There are four stages for a leg to move forward

1) Femur raising.
2) Tibia moving forward.
3) Femur lowering.
4) Tibia moving backward.

This is the sequence for the leg to move forward , substituting stage 2 and 4 we obtain backward movement. These are the fundamental movements for each leg, to make the robot move in all direction we have to coordinate the two leg step sequence. The implemented step sequences to move forward are similar to the arms coordination during two different swimming style: free-style and butterfly-style in which the two arms respectively have 180° or 0° phase difference, while to change direction one leg moves forward and the other backward. In this way each PLIF can potentially be moved in every direction of the plan.

4. DYNAMIC MEASURES

Several different experimental tests have been performed on the robots, in order to verify the design hypothesis. As a result it has been observed that the real PLIFs behavior is far away from the expected one, seldom the desired direction and the effective movement of the robot are the same, for almost every frequency the real direction of the robot remains the same whatever the one imposed by the control algorithm is. A great role in the movements is given from the various characteristic modes of the ground-leg system that could be differently excited in the frequencies near resonance. In fact a small change in the step frequency around 1kHz causes the robot to move forward, left, backward, right even if the algorithm impose always the forward movement.

This behavior is due to the fact that a leg can be more activated than the other at a certain frequency, and it is difficult to find a reliable theoretical model of the robot movement, because we must contemplate leg-ground interactions and the leg characteristic frequencies that change above mounting.

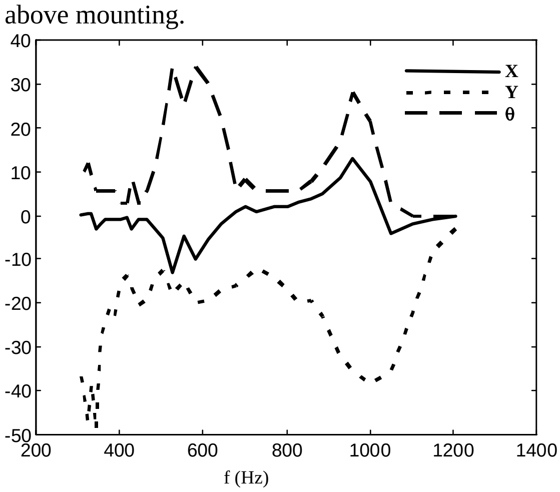


Fig.5 Final position, X Y (mm), and orientation, θ/2 (degree), of the robot, after 200 steps of forward command , as a function of frequency.

In order to identify the robot behavior, several dynamic measurements have been performed. In particular the acquisition of the robot movements after 200 steps in each directions, using a 90V voltage supply, for various frequencies have been done. In Fig. 5 the results of one of these measurements are reported. The considered three degrees of freedom were the planar position of the middle-point beneath the legs (X,Y in mm) and the direction angle (in degree, scale 1:2), assuming that the initial position was X=0, Y=0, θ=0.

We wish to point out the resonance peaks in which the robot move very fast (up to 18 cm/s) but tripping without control.

5. INFRARED INTERACTION

As a consequence of the results of the previous section, in order to achieve reasonable movements, some kind of feedback should be given to the robots. Due to the small size and weight it appears illogical to adopt sophisticated sensors, moreover to make the PLIFs autonomous communications with external devices should be avoided. For these reasons the adoption of small infrared sensors mounted on board on the robots has been chosen. Moreover, since the study of the cooperation between various microrobots is one of the most important aim of this project, for the interaction among the robots, two phototransistors have been fixed on the PLIF I and an infrared led on the PLIF III to know the relative position between the two robots. Small components with a view angle of 18° that allows greater accuracy in the positioning have been used. The phototransistors were fixed on the front of the robot and separated by opaque material to improve the difference between the right and left signals (Fig. 2a).

A simple algorithm to make PLIF I catch PLIF III has been implemented: it makes the robot turn on the more enlighted side and go straight ahead if the ‘eyes’ are equally excited (Fig. 6).

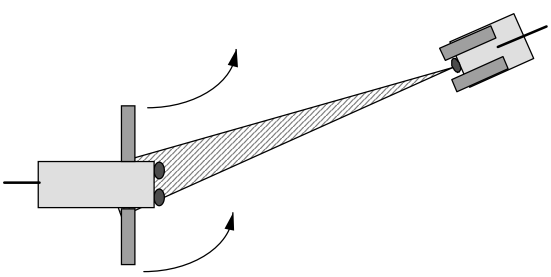


Fig 6. PLIF I catching PLIF III (upper view).

These digital conditions are fuzzyfied using two threshold to implement concepts of the distance and orientation between the two- robots.

After the set-up of the algorithm and the thresholds values, the result was that PLIF-I could catch PLIF-III quickly and with good precision.

6. Self learning

6.1 Introduction

Dynamic measures point out how difficult it is to find the frequencies in which the robot behave as we want. But in limited frequencies and movement styles, the robot has quick and precise movements in every angle and direction besides the cardinal ones. The problem is how to fix the frequencies and the movement sequence that imply the desired direction and angle. In fact those unknowns depend on various parameters such as supply, carried-weight, steepness of the ground and kind of surface the robot walk on. This strong dependence on various parameters that may change with time doesn't allow the robot setting once and for all.

In our experiments the goal of the robot is to reach a target represented by an infrared light source, eventually with some obstacles in the path. In particular we want the robot to choose by itself the right frequency and movement style to achieve the goal, so that the robot can do a self-test of the operative conditions and choose the new best value for the unknowns if some parameters change.

6.2 Fundamental principles

Learning problem is much more complex if it is applied to a real robot instead of using a robot behavior simulation with an algorithm, in fact there are a lot of influencing parameters, often unknown [13],[14].

The objective of the designer is to find the control function $f: S \rightarrow A$, that for each state of the robot (S) gives the right movement (A). This is possible only if the task of the robot is simple, if nothing changes in the influencing parameters and if the relation between the robot state and the sensor signal is known. If the robot has to face unexpected events it must be able to self learn how to reach the goal.

Learning means the ability to increase our knowledge and skills by the results of the experience, that is characterized by the presence of an aim and an evaluation criterion of the actions done in its achievement. How is it possible to fix an evaluation criterion for the single action if the aim function has a peak in only one configuration that may be achieved after several steps ? In this case we can know nothing about the effectiveness of the intermediate actions until we achieve the goal, in fact only at the end of an experiment we can determine if it was successful or not.

We search, initially the function $Q: S{\times}A \rightarrow E$ where E represents the effectiveness of the action A if the robot is in the state S. The function f (control law) can be then extrapolated from function Q by picking for each state the more effective action.

Now we have to change E values on the basis of experience. The codominion of the function Q is stet randomly or on the basis of acquired knowledge, then if the robot is in the state S_j it perform the most effective action A_j reaching the state S_{j+1}.

This process stops when the robot reaches the goal or the number of steps becomes too big, then the effectiveness E of the actions will be consequently changed.

This technique is called '*reinforcement learning*' and it permits to quickly achieve a good knowledge of the right behavior by an autonomous training of the robot.

This algorithm can operate in the following frames with external or internal supervisor or without supervisor, as regards the learning process control, and with an award during the learning session or with an award after the learning session,

as concerns the instant in which the training action is applied.

Lesson means a single sequence of action after which the effectiveness E of the action will be increased or decreased, depending upon the achievement of the goal.

Usually the learning process is more difficult and slower with an unsupervised algorithm and premium after lessons, because it is much more difficult to understand how a past action has been determinant to reach the goal.

In this kind of algorithm a large number of lessons are normally required before the robot learn, that is why this algorithm has been prevalently used in simulation works.

6.3 Application to the PLIF

To face the robot learning problem, the '*reinforcement learning*' technique that search for the Q function and allows the robot to train itself autonomously and with deferred premium without supervisor, has been employed [15]. In our case an experiment consists in a sequence of steps that a PLIF executes in order to reach the target, represented by an infrared light source. However the PLIF does not know its state but only the sensor measurement ; for this reason it was assumed as an estimate of the state of the robot, the measure of the two sensors that approximately gives the robot position with respect to the target.

The Q-learning process has three main problems:

1) the discretization of the state space ;
2) the necessity to operate on each sequence to reach the optimum ;
3) the difficulties to judge the effectiveness of a single intermediate movement inside a long sequence.

The first problem implies the choice of the number of cells in which to divide the state space. This number is chosen on the basis of learning speed, movement precision, noise, calculator power. For our robot the signal of the two phototransistors has been divided in 16×16 cells. The second problem is connected to the others, in fact to reach the ‘optimum’ it would be necessary for the robot to do infinite sequences over infinitesimal state cells. However it would be necessary an infinite time to reach the optimum, because after a normal training period some redundant movements exist, anyhow bringing the robot to the goal. To overcome this problem we can reward the sequences without replying movement and leading more quickly to the goal. To overcome the third problem we can give greater importance to the last steps by increasing the rate of E changing.

A learning session consists in initializing the Q function randomly, then performing several sequences of experiments and learning until a good result is achieved. Many learning sessions have been performed, obtaining quickly good results. In particular the robot learns in 20 lessons to reach the goal within 1cm and after 100 lessons the robot is well trained in order to reach the goal in the range of action of the sensors (about 6-7 cm).

Each lesson lasts a few seconds, so a complete learning session should last few minutes, allowing the robot to quickly set-up each time the operative conditions change.

The robot has been also trained to overcome an obstacle in the direction of the goal obtaining analogous results initializing also in this case randomly the Q-function.

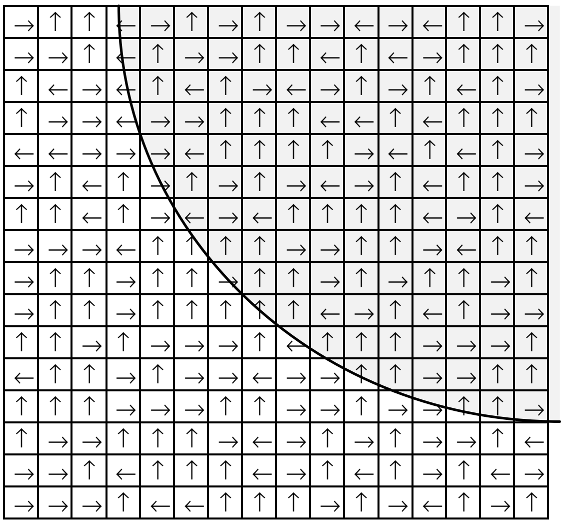
It is interesting to point out how the robot is able to accomplish complex maneuvers to overcome the obstacles. Such maneuvers would be very difficult to implement in a static algorithm. If we use for the same task a robot trained without obstacles the learning time is increased due to the fact that E values during the past lessons had increased too much to be quickly changed.

It must be avoided that those values could grow so differently by implementing a saturation during the learning process.

In Fig.7 the control law as a function of the state, divided in 16x16 cells, at the beginning of the learning session is shown. Each cell represents a particular light level of the two phototransistors and to each cell is associated the best movement, i.e. the one with the greater value of effectiveness E , that is randomly initialized and changed at the end of each lesson.

After the learning process of 100 lessons, the arrows on the state space are distributed more uniformly (Fig 8).

The represented matrix gives us the function f which characterizes the best movement to reach the goal for each state in the cell where the robot is.



↑ Forward ← Left →Right

Best movement (Max E) for each state-box

Fig.7. Control law random initialization.

In reality only the bottom left of the matrix (the part not shaded in the figures 7 and 8) has been affected by the learning process, because the possible combinations of the transistor signals lay there. As it was expected, turn left movements are more concentrated left high, while turn right movements are more concentrated right bottom.

The forward movement has the best effects on the reaching of the goal as it is uniformly distributed over the matrix.

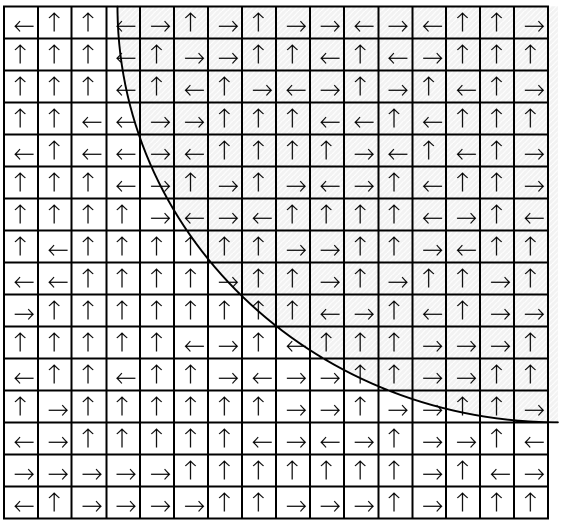


Fig.8. Control law after the learning process

We wish to point out that the ‘Turn left’ movements in the bottom-right zone and the ‘Turn right’ movements in the high-left zone don’t represents errors of the learning process but the movements that avoid legs slipping and drive the robot quickly to the goal.

These movements are the most important in this kind of algorithm because they are very difficult to be discover and then to implement on a standard movement algorithm.

7. CONCLUSIONS

In this paper we have shown the possibility of using piezoelectric materials for precise microrobot locomotion.

Thanks to their high frequency range, these actuators allow PLIF to move quickly in all directions, up to 18 cm/s. At the same time it is very accurate in positioning : each step move the robot 40μm forward and it is easy to lower down the positioning resolution to few microns using not the walking of the robot but the piezoelectric bending, a quadratic function of voltage.

Due to robot dynamic behavior it is necessary an accurate setup of the structure of the robot to maintain a perfect symmetry and avoid uncontrollable movements of the PLIF II.

Even if in the actual implementation the robot are wire connected to an external controller, the supply and control have been designed for a future integration on board on a single custom-chip, avoiding complex solutions.

Dynamic measures demonstrated that open loop control is impossible due to the extreme difficulties in identifying the relations between direction, velocity and the influencing parameters.

To overcome this problem we implemented the '*Q*-learning' self-learning algorithm that permits the robot to find quickly and autonomously the right movement sequences.

Further study is in progress to investigate about the possibility for the robot to recognize the type of surface from to the observation of a signal on the still leg, caused by the vibrations forced by the other leg. In fact the signal waveform changes with the kind of substrate, so it is possible for the robot to recognize the ground in which it walks, by examining those signals and to change the movement sequence accordingly.

Another improvement could come from the application of neural nets during the learning process [14]. In this case the robot could learn autonomously the best sequence to be sent to the four piezoelectric parts to move along the desired direction.

Further and updated information concerning PLIF microrobots can be found in the WEB page

http:\\www.scg.dees.unict.it

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