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Simulator for Learning Symbolically about the Behavior of Motion in Bipedal Robots*

FERNANDO RAMOS, SANDRA LÓPEZ, ENRIQUE ESPINOSA, JOSÉ CARLOS REBÓN, ALEJANDRO HERNÁNDEZ and ABEL ARREDONDO
Tecnológico de Monterrey Campus Cuernavaca, Mexico. E-mail: enrique.espinosa@itesm.mx

The main objective in developing the simulator presented in this paper is to assist undergraduate students to learn about the analysis of motion behavior in bipedal robots by exploring an approach based on fuzzy-symbolical variables. This approach facilitates learning about and understanding of motion behavior using symbolic reasoning instead of numerical reasoning, such as that based on the analysis of moments and forces, which are difficult to grasp. An important educational aim of this simulator is to develop cognitive skills such as analysis, the construction of structures and generalization. In addition, the simulator helps students to develop an aptitude for self-directed learning as the students themselves build the rules that help them to understand the behavior of motions. The simulator has been built to interact with two real bipedal robots that have 12 degrees-of-freedom (DOF). Experimental results showed that the students were able to understand and analyze motion behavior and then predict the risk that the robot would fall as they interacted with the simulator by reasoning using symbolical variables and their relations. In addition, students developed their cognitive skills throughout the learning process.

Keywords: cognitive skills; bipedal robots; robot motions; fuzzy relations

INTRODUCTION

The context

SEVERAL METHODS HAVE BEEN DEVELOPED to study the dynamic balance of bipedal walking robots. These methods are related to classical approaches, which are mainly based on the concept of the zero moment point and the center of gravity. These approaches are based on the analysis of moments and forces, which include the difficult task of analyzing the parameters involved in motion behavior. Alternative approaches that use soft-computing methods and those extracted directly from human behavior have also been proposed. The work presented in this paper focuses on the development of a simulator to assist students in the analysis of the relevant parameters involved in the motion behavior of bipedal robots using reasoning with fuzzy-symbolic variables, and in this way it facilitates learning about and understanding the task.

The present work is related to alternative approaches to the learning and teaching of robotics. For instance, an alternative way of teaching robotics is proposed that exploits the multidisciplinary character of the field of robotics [1]. Other approaches are related to learning by the making of prototypes and then teaching pupils [2]. Interaction with intelligent devices teaches the student that robot autonomy has an important role in the scientific exploration of Mars [3]. An important educational aim of the current work is to use simulators to assist students to learn about the motion of bipedal robots by interacting with them using symbolic reasoning. The acquisition of robotics skills using simulations is an example of the use of symbolic representation from the point of view of semiotic interactionism in which the notion of the dialectical interplay between symbol and thought is key to the concept development, since there seems to be an interaction between symbol and thought when one compares representations across media, such as language, dance, music, drawing, and computer simulations. Other scientists have proposed the notion of scaffolding [5], pointing to the assumption that all knowledge is social in nature, so that all learning takes place in the context of social interactions that lead to understanding. Presenting robotic motion in a graphical–symbolic way makes it more social than abstract, and thus easier to understand.

Throughout this paper, it is considered that it is necessary to develop cognitive skills in order to understand how complex systems, composed of a significant number of parameters and their relationships, work. In particular, in the motion of bipedal robots discussed in this work, the student should be capable of abstracting the relevant parameters involved in motion behavior through the correct analysis. A behavioral perspective of the robot's motions needs the correct relationship between the parameters to be considered; the need to learn how to build these structures is evident. In addition, the fact that the students themselves build the rules that give the behavior of the motion, taking into account the parameter values

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and their relationships, means that the simulator helps motivate self-directed learning, which is an important educational concern.

Background

A 'posture' is defined by the set of joint values of a robot at a given moment. Thus, a sequence of postures defines a motion. The problem of determining sure motion in bipedal robots has been tackled using several approaches. Vukobratovic and Borovac point out that, apart from the realization of the relative motion of the mechanism's links, the most important task of a locomotion mechanism while walking is to preserve its dynamic balance, which is achieved by ensuring the foot's whole area is in contact with the ground [1]. Since a biped robot tends to tip over easily, it is necessary to take stability into account when determining a walking pattern [2]. Goswani refers to the importance of a thorough analysis in order to enhance prediction and eliminate the possibility of falling, in addition he emphasizes that the postural balance and stance foot equilibrium are profoundly inter-twined [6].

Several methods have been developed for studying the dynamic balance of walking sequences and postures of bipedal robots. These methods are related to classical approaches and are mainly based on the concept of the zero moment point and the center of gravity.

The study of the dynamic balance of bipedal robots in classical approaches is related to the zero moment point (ZMP) and the center of mass (COM) [6, 8, 9]. Takaneshi [10, 11] has proposed the concept of the security polygon, which is formed by linking the extreme points of the feet to build a polygon. If the centre of mass of the robot lies within this polygon then the posture is a sure one.

While classical approaches have contributed significantly to the study of dynamic equilibrium, alternative approaches based on soft-computing models have been explored to solve different problems associated with the locomotion of bipedal robots. Zhou *et al.* [12, 13] have proposed a fuzzy approach to tackle the problem of gait synthesis for bipedal robots. Park [14] proposes a fuzzy-logic zero-moment-point (ZMP) trajectory generator that would eventually reduce the swinging motion of the trunk.

The work of Kati and Vukobratovic [15] focused on a survey of the application of intelligent control techniques (neural networks, fuzzy logic and genetic algorithms) and their hybrid forms (neuro-fuzzy networks, neuro-genetic and fuzzy-genetic algorithms) in the area of humanoid robotic systems. This survey aimed to demonstrate the advantages and disadvantages of the application of intelligent control techniques in this area.

Other approaches are based on the analyzing a human walk. In [16] a method is proposed to extract the motion primitives by analyzing the trajectories of the limbs. In [17] the body motions of a humanoid robot are generated by imitating human dances. Motions are acquired through a motion capturing system that provides motion primitives that are related to arm and step movements. The joint angles that are generated should satisfy the mechanical constraints that are associated with the ZMP of the robot. The generated motions were successfully performed by a real robot.

The problem

The analysis of the dynamic behavior of motion under classical approaches, based on forces and moments, is quite complex and becomes more complex as the number of joints increases.

The proposed solution

The proposed solution is to develop a simulator based on alternative approaches in order to simplify the analysis by taking into account relevant parameters that influence the dynamic behavior of the movements represented by a sequence of postures.

Most of the approaches mentioned above are not concerned with the relations between relevant parameters that could influence the generation of risky postures. In this work, a set of relations are established to build a framework to aid in the analysis of the dynamic behavior of bipedal robots to detect and predict risky postures in movements that have already been generated and are being generated. In order to achieve this, a fuzzy approach is proposed that is based on the relationship between parameters associated with those segments of the legs that are projected into both the Y–Z and the x–z planes and the ankle angles, which are among the most important. For instance, vectors representing the legs of the robot are fuzzyfied in order to facilitate the generalization of the different configurations that the robot adopts. A sequence of postures is generated that are then dynamically analyzed through relations between the parameters that have been symbolically fuzzyfied.

Using the fuzzy-vectors that represent the legs and feet of the real robots, a simulator that describes the motions made it, both in the Y–Z and the x–z planes, has been developed. The simulator can receive and load files that have been generated for the movements of the robot and then display and reproduce them. Based on the simulated postures, fuzzy relations between the parameters mentioned above are built in order to identify, and identify and classify, risky and sure postures so that dangerous postures that could lead to a fall during a walking sequence could be detected and then corrected in time to avoid the fall happening.

The objectives

The main instructional objective in this work was to motivate students in the development and use of simulators as an aid to assist them in

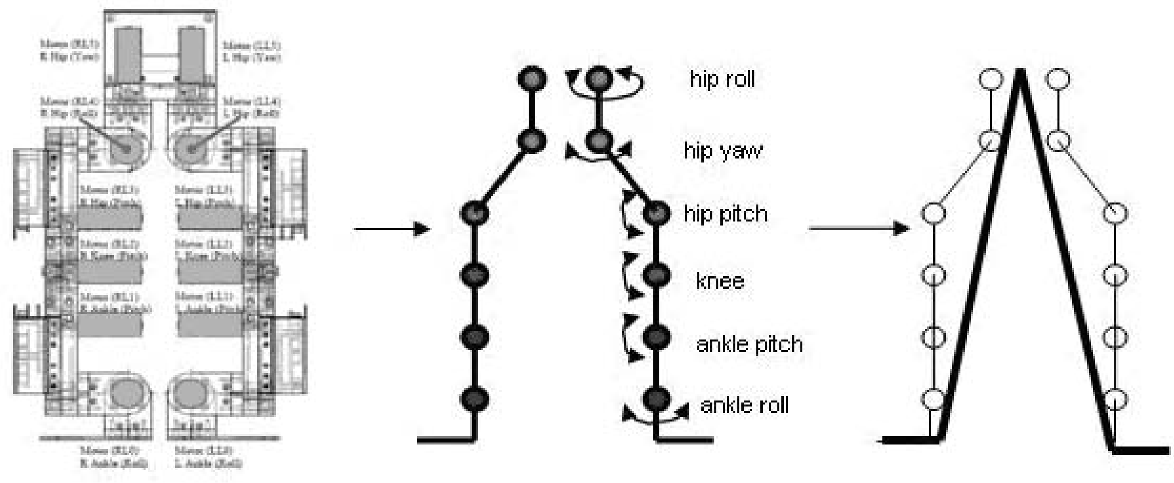

Fig. 1. The e-nuvo (ZMP Co) robot and its representation by vectors.

learning difficult-to-understand concepts. Another important objective was to develop the cognitive skills that are needed in order to learn and understand the behavioral aspects of the movements of bipedal robots. These cognitive skills are: analysis, construction of structures, and generalization.

The simulator has helped students to learn the concept of preserving the equilibrium of bipedal robots while in motion, as well as reasoning with the symbolical data through learning a soft computing approach such as fuzzy reasoning. Both concepts are part of the mobile robotics course in the undergraduate engineering program of mechatronics and computer sciences.

The simulator proposed in this work does not pretend to replace the concept of ZMP in the study of motion equilibrium in bipedal robots, but motivates the students and helps them to understand the problem by investigating it in other ways. Once the students understand the problem of the inter-relationship between important factors (parameters) that have to be taken into account in the study of motion using the simulator, the next step is to study the equilibrium problem using the ZMP numerical approach. What is unique in this simulator is its ability for symbolic reasoning for which the students need to build the symbolical rules that relate the relevant parameters in order to understand the problems of maintaining motion equilibrium.

THE SIMULATOR

The robot used for the experimental part of this work was the *e-nuvo (ZMP Co)*. It is a bipedal walking robot with 12 DOF (6 DOF per leg), and is 30-cm tall and weighs 1.35 kg. Figure 1 shows the robot and its representation based on vectors, which are then fuzzified.

The robot is controlled through the serial port of a PC, by means of a friendly e-nuvo Graphical User Interface (GUI). The motion files with which the robot's movement was programmed are briefly explained in the next section.

Knowing that one problem of bipedal robots is the continuous risk of falling during walking sequences, a study of every posture during a walking sequence could help to deduce a tendency. The analysis of every posture was made according to a fuzzy model that was planned based on the concept of risky and sure postures. The idea was to create a simulator that could graphically represent the bipedal robot, in a two-dimensional reference, and to include the fuzzy analysis with which every posture could be classified. A two-dimensional reference was generated with the vector decomposition of the robot that had previously been completed: hence the term fuzzy-vector. See Fig. 2.

Characteristics of the simulator

- *Graphical robot representation:* plane *X–Z;* plane *Y–Z*.
- *Context of the analysis:* relevant parameters for motion behavior; relationship between relevant parameters; fuzzy-symbolical reasoning for the construction of rules that express the behavior of motions.

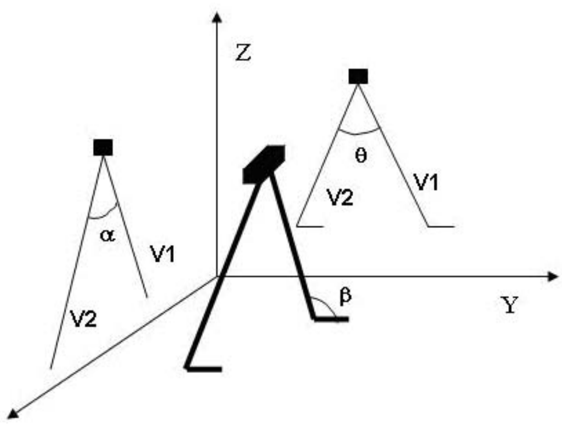

Fig. 2. The projection of vectors representing legs into planes *X–Z* and *Y–Z*.

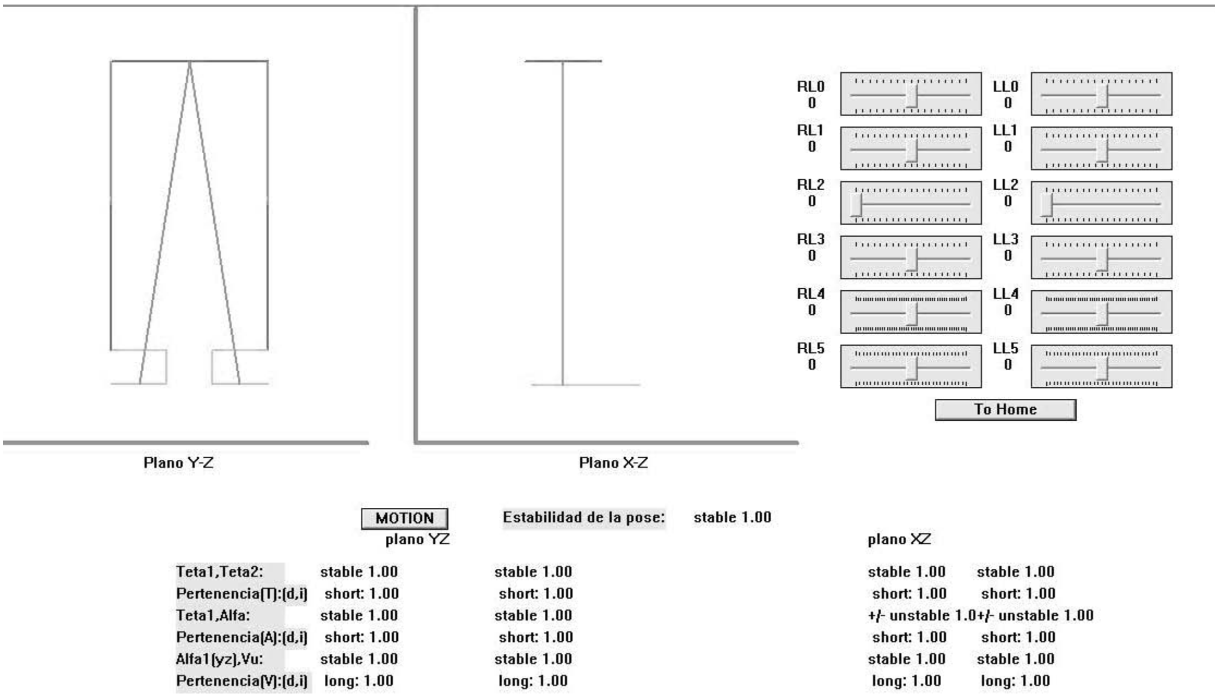

Fig. 3. Simulator display screen.

- *Basic concepts of motion behavior based on postures:* stable, more or less stable, more or less unstable, unstable.
- *Input and output data:* motion files to be reproduced in both planes (*X–Z, Y–Z*). For instance, the simulator analyses each of postures belonging to a given sequence (several hundred postures are needed), and classifies them according to the model that has been programmed into the simulator.

An image on our simulator's screen is shown in Fig. 3. In the right-hand panel we can see a set of trackbars, whose function is to permit the movement of every single joint of the robot. Each bar has a range of movement that can go from 0° to 180°, from –80° to 80°, from 0° to 120°, and from –20° to 80°, depending on the selected joint. These bars read the values at which the user sets them and send that value to the corresponding joint. The 'MOTION' button on the lower-center section of the main frame starts the robot movement.

Below the 'MOTION' button, the result of the fuzzy analysis is shown. That is, the result of the last posture the robot adopts from the motion file is displayed, being either stable, +/- stable, +/- unstable, or unstable, and the degree of membership to that concept.

THE FUZZY FRAMEWORK

The concepts to be fuzzyfied are (see Fig. 4):

- First leg (right leg in the plane *X–Z*) and second leg (left leg in the plane *X–Z*);

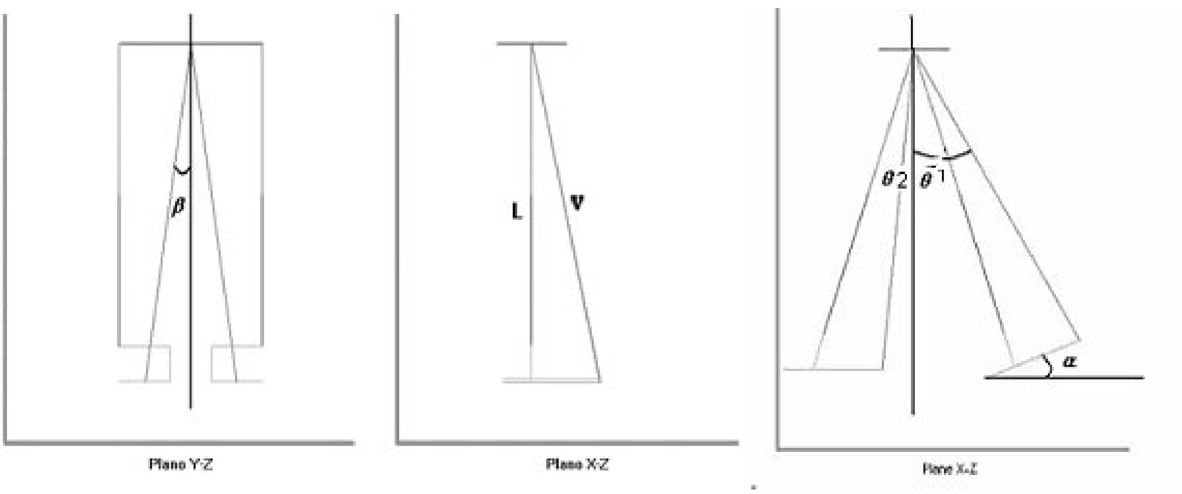

Fig. 4. Distribution of the fuzzy variables that were selected.

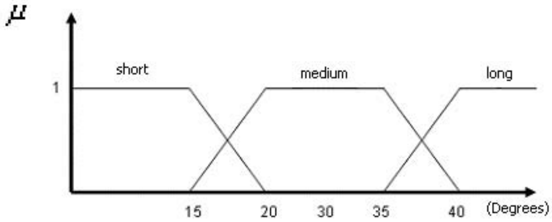

Fig. 5. Membership function for the variables measured in degrees (θ_1, θ_2, α, β).

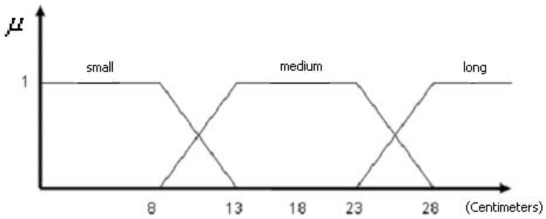

Fig. 6. Membership function for the variables measured in centimeters (V, L).

- θ_1: First leg's opening angle referred to an imaginary vertical line that crosses the robot from a point situated at the middle of the hip of the robot;
- θ_2: Second leg's opening angle referred to the same imaginary line mentioned above;
- *L:* Resulting Vector rectangular component, projected onto the imaginary vertical line;
- *V:* Resulting Vector of the graphical sum of the individual leg's segments vectors;
- α: Rotation angle of the ankle with respect to the ground;
- β: Opening angle of the first leg, referred to a vertical imaginary line that bisects the robot from the middle of the robot to the ground on the Cartesian plane, which does not belong to the current robot's view.

Figure 4 shows the distribution these variables on the legs of the robot.

For variables measured in degrees, the membership function of the term is defined in Fig. 5.

This means that, for angles between 0 and 20°, the fuzzy value was determined as short. For angles between 15° and 40°, the fuzzy value is medium. For angles of 35° and more, the fuzzy value is long. The same applies for negative values: for angles between 0 and –20°, the fuzzy value is 'minus' short, for angles between –15° and –40° it is 'minus' medium, and for angles smaller than or equal to –35° the value is 'minus' long.

The membership function for the vector magnitudes is defined in Fig. 6.

The same applies in this case, except that the measures are in centimeters. As a brief example, for vector magnitudes between 0 and 13 cm, the associated fuzzy value is *small*. Let's recall that the maximum length of a leg is 30 cm. So the fuzzy definitions are defined by considering this maximum length. In this case, there can be no negative vector magnitudes, so the fuzzy values remain positive.

The importance of the functions above should be emphasized because they will be the basis of our model. That is, a set of *stability matrices* will be created by which every posture can be described depending on the value of the variable analyzed.

Fuzzy relations

Given that the reasoning mechanism is based on fuzzy relations, the following expressions are used to obtain the membership of the relation between two variables belonging to two different universes of discourse. Expression (1) shows the member function that relates two fuzzy variables belonging to two different universes of discourse (X and Y):

$$R = \{(x, y), \mu(x, y))|(x, y) \in X \times Y\}. \quad (1)$$

By transitivity we are able to relate three universes of discourse as follows:

Let $R1$ and $R2$ be fuzzy relations defined in $X \times Y$ and $Y \times Z$, the min–max composition of $R1$ and $R2$ is a fuzzy set defined by:

$$R1oR2 = \{[(x, z), \max\min(\mu_{R1}(x, y), \mu_{R2}(y, z))] \\ |x \in X, y \in Y, z \in Z\}(2)$$

in terms of its equivalent member function of the resultant relation:

$$\mu_{R1oR2}(x, z) = \max\min[\mu_{R1}(x, y), \mu_{R2}(y, z)]. \quad (3)$$

The last expression relates, by transitivity, two fuzzy variables, x and z, belonging to two different fuzzy sets through a fuzzy set common to them.

Having defined the membership functions, the relations among them must now be established, and a selection made of those with which the work will continue, prioritizing their importance to the posture. Based on an important experiment performed with the robot, it was determined that the most important relations are as follows: θ_1 **related to** θ_2; V_1 **related to** α_{yz}; α_1 **related to** θ_1. The reduction in the number of variables was made because it was noticed that the rest of the variables are contained in those three relations, and indirectly participate at the same level along with those variables in the stability of the posture. With these relations, a set of matrices that describes the stability was generated.

Classification of postures through generalization concepts

For practical reasons, four basic fuzzy concepts related to the stability concept were proposed, in the expectation that a number of the postures analyzed could fall into them. These are: stable, +/− stable, +/− unstable, unstable. A stable posture is one in which both legs of the robot are in contact with the ground, and where the angle of aperture of the legs does not exceed a certain range. Depending on how steady the robot

Table 1. Matrix frame 1. Relation between θ_1 of the right leg and θ_2 of the left leg in *X–Z* plane.

θ_1^{right} / θ_2^{left}	–BIG	–MEDIUM	–SMALL	SMALL	MEDIUM	BIG
–BIG	stable	+/– stable	+/–unstable	+/–unstable	+/–unstable	+/–unstable
–MEDIUM	+/– stable	stable	+/– stable	+/– stable	unstable	unstable
–SMALL	+/–unstable	+/– stable	+/– stable	stable	+/–unstable	unstable
SMALL	+/–unstable	+/– stable	stable	stable	stable	+/–unstable
MEDIUM	+/–unstable	unstable	+/–unstable	stable	+/– stable	+/–unstable
BIG	+/–unstable	unstable	unstable	+/–unstable	+/–unstable	+/– stable

XZ

Table 2. Matrix frame 2: Relation between α_1 and θ_1 of the same leg, in the plane *Y–Z*.

θ_1 / α_1	–BIG	–MEDIUM	–SMALL	SMALL	MEDIUM	BIG
–BIG	X	X	X	X	X	X
–MEDIUM	X	+/– stable	+/– stable	+/–unstable	+/– stable	X
–SMALL	X	+/– stable	stable	+/– stable	stable	X
SMALL	X	stable	stable	stable	+/– stable	X
MEDIUM	X	stable	stable	+/– stable	+/–unstable	X
BIG	X	+/– stable	+/– stable	+/–unstable	unstable	X

YZ

Table 3. Matrix frame 3. The rules of stability between two relationships.

	STABLE	+/– STABLE	+/–UNSTABLE	UNSTABLE
STABLE	stable	stable	+/– stable	+/– unstable
+/– STABLE	stable	+/– stable	+/– unstable	unstable
+/– UNSTABLE	+/– stable	+/– unstable	+/– unstable	unstable
UNSTABLE	+/– unstable	unstable	unstable	unstable

appears, the posture can acquire a degree of membership of between 0 and 1, where 0 is the lowest degree of membership, and 1 is the highest degree of membership.

Stability matrixes

The matrices that relate the selected variables in a stability model were established through a visual analysis, using both the simulator and the robot An example of such a matrix is the following: a matrix expressing the relationship between the opening of the legs of the robots in the plane *X–Z*.

Table 2 shows the relationship between the opening angle of the legs of the robot, and the opening angle of the foot with respect to the ground. As in the previous case, some cases are impossible to implement because of the mechanics of the system, so they are not considered in the model, and are marked with an X.

Table 3 showing Matrix frame 3 illustrates the relationship of stability between the results of two relationships.

The following relevant relations contribute considerably to the motion behavior: θ_1 **R** θ_2, V1 **R** α_{yz}, θ_1 **R** α_1. From a practical point of view, the most important of these is V1 **R** α_{yz}.

EXPERIMENTAL CONTEXT AND ANALYSIS OF RESULTS

Experimental context

- *The topic to be learned*: Motion behaviors in bipedal robots.
- *Learning approaches used*: The classical approach based on the analysis of forces and moments and the simulator using fuzzy-symbolical variables.
- *Number of courses given*: Four for the classical approach, six for the alternative one.
- *Number of students taking the course*: About 80 for the classical approach, 120 for the alternative approach.
- *Way of working*: Groups composed of three or four students working in a collaborative way.
- *Number of sessions for teaching the topic*: Six for both approaches.
- *Duration of sessions*: 90 minutes each for both approaches.

On a course taught using the classical approach, the instructor delivers a lecture in which the concepts are presented in a text-book fashion, and formalisms appear from the beginning. On the alternative approach, the instructor fosters a workshop-style environment in which the students make use of the simulator and learn about the concepts, without resorting to their underlying formalisms. Rather, they view symbolic data and observe graphical simulations, which allow them to understand the concepts.

The sessions of the *alternative approach* were as follows:

- *Session 1*: Explanation of the problem of bipedal robots during motion: students already have a background in the kinematics of robots and walking routines in robots with legs, such as hexapods and quadrupeds.
- *Sessions 2, 3*: Teaching fuzzy reasoning, with a particular interest in fuzzy relations.
- *Session 4*: Motion programming in real bipedal robots and how the simulator works.
- *Sessions 5, 6*: Construction of fuzzy rules that support the interrelations between the factors that affect the equilibrium of the robot during motion.

The sessions of the *classical approach* were as follows:

- *Session 1*: Explanation of the problem of bipedal robots during motion: students already have a background in the kinematics of robots and walking routines in robots with legs, such as hexapods and quadrupeds.
- *Sessions 2, 3, 4*: Analysis of forces and moments acting on different parts of the bipedal robot.
- *Session 5, 6*: Analysis of balance equilibrium of Vukobratovic and the Security Polygon of Takanishi [7].

The learning controls to be considered in the experiment

Five relevant concepts that had to be learned served as experimental controls in the learning process. The controls used to compare the learning performances of the two approaches are related by a progressive learning of the concepts. These concepts are learned sequentially through a process that is described step by step below.

Step1 (experimental control 1: learning about the concept of posture) → ***Step2*** (experimental control 2: learning about the concept of a sequence of postures) → ***Step3*** (experimental control 3: understanding isolated relevant concepts involved in motion behavior) → ***Step4*** (experimental control 4: learning to build relationships between relevant concepts, a structural view) → ***Step5*** (experimental control 5: learning the concept of stable and/or unstable robot motion applying generalization mechanisms).

It has been observed that the concept learned in ***Step2*** depends on the concept learned in the ***Step 1***, and so on.

Table 4. Comparison of the two approaches based on the experimental controls described in the step-by-step process described in the text.

Process	**Experimental control**	**Numerical classical approach (forces and moments)**	**Symbolical alternative approach (simulator)**	**Comparative analysis**
Step1	Learning the concept of posture	100%	100%	Both approaches give 100% in performance because the definition of posture is relatively easy to understand.
Step2	Learning the concept of sequence of postures	100%	100%	Both approaches give 100% in performance because the definition of posture is relatively easy to understand.
Step3	Understanding relevant concepts involved in motion behaviour	60%	95%	The performance of the symbolical approach is 35% better than that for the classical approach. The 40% of the students following the classical approach found that the relevant concepts based on forces and moments are hard to distinguish because of the difficulty of the equations.
Step4	Building relationships between relevant concepts (structural view)	40%	90%	Approximately 60% of the students following the classical approach found that the complexity to understand relationships between isolated concepts is even greater when forces and moments need to be related. The performance of the classical approach tends to decrease as the complexity of concepts increases.
Step5	Concept of stable and/or unstable robot motion	30%	90%	The tendency to decrease the learning performance in the classical approach is reaffirmed as the complexity of equations based on forces and moments increases. On the other hand, using fuzzy reasoning interacting with the simulator helps students to understand these concepts because it is quite similar to the qualitative reasoning used by humans.

ANALYSIS OF RESULTS

Learning assessment: Classical approach versus alternative approach

The comparison is shown in Table 4, where experimental controls are associated with the concepts to be learned. The percentages shown in the table have been rounded in order to facilitate the comparison between the approaches.

Based on the experimental controls proposed as elements to assess the learning performance of both approaches, we have confirmed that as the process got close to Step5 (concept of stable or unstable robot motion) the complexity of the equations based on forces and moments increased, which made the understanding of concepts using the classical numerical approach very complicated. On the other hand, interacting with a simulator based on fuzzy symbolical reasoning, which is similar to that used by humans, facilitated the task of understanding the concepts related to the steps of the learning process. The tendencies in learning performance for both approaches are illustrated in Fig. 7.

As specified in the introduction to this paper, we are concerned with three cognitive variables: analysis, construction of relations and generalization. We argue that analysis is the cognitive variable that supports the construction of relations and supports the mechanism for building general rules that aim to establish the concept of stable or unstable robot motion. These variables have been evaluated for students who followed the learning process using the simulator based on fuzzy variables. Eighty students participated in this approach. We now describe how the cognitive variables have been hardwired into the students' skill-set as the steps of the process described above progress.

Given that five concepts, corresponding to the experimental controls described above, should be learned, a set of exercises were given to the students in order to measure the cognitive variables.

Measurement of cognitive variables

The measurement of the identified cognitive variable analysis took place from the third experimental control.

Exercise: Interacting with the simulator to extract the most relevant variables involved in the motion behavior of the robot.

Observation: Six variables were involved as described in 'The Fuzzy Framework' section. These variables were then fuzzyfied in order to convert a numerical variable into a fuzzy symbolic one.

Results: 95% of the students (76/80) got the six variables; 90% (72/80) of the students could fuzzyfy the six variables.

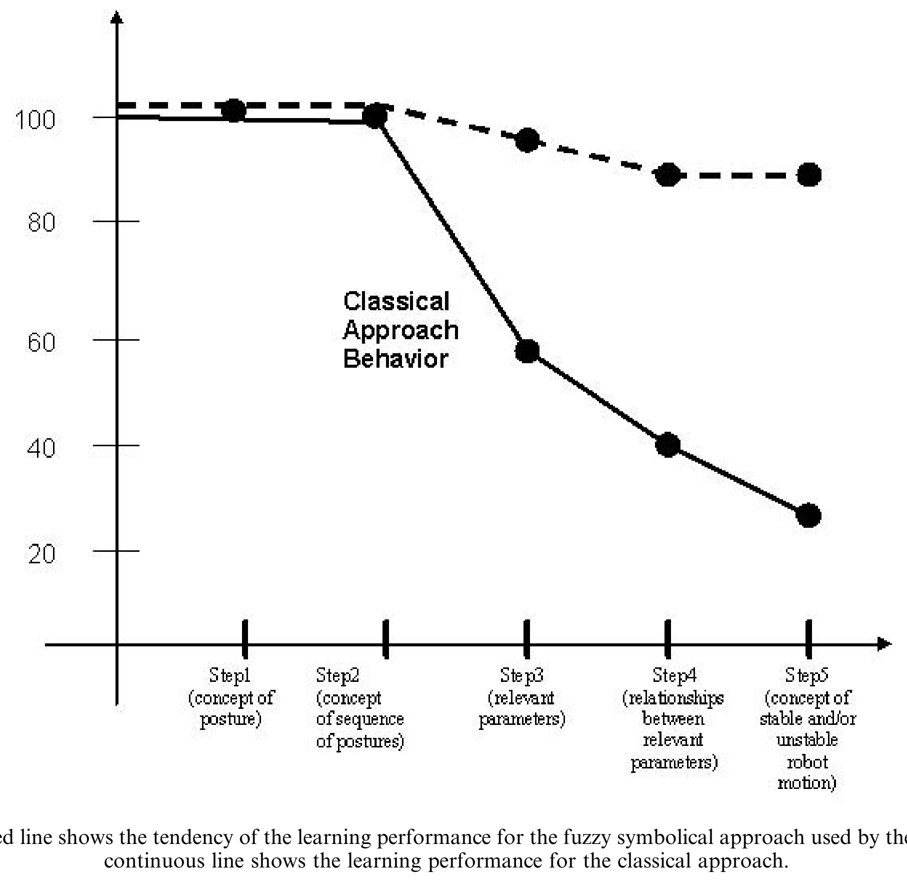

Fig. 7. The dashed line shows the tendency of the learning performance for the fuzzy symbolical approach used by the simulator. The continuous line shows the learning performance for the classical approach.

Comments and interpretations:

- If 95% of the students got the six variables, then it means that they were able to extract the total of variables due to a good analysis aided by the symbolical approach graphically illustrated by the simulator.
- The 10% of students who had incorrect results found that the fuzzification process was a new concept and not easy to understand at the beginning.

The next measurement was related to the cognitive variables: analysis, construction of relations and rules of generalization related to the robot motion. This measurement took place at the fourth experimental control.

Exercise:

- Interacting with the simulator to establish relations between the variables that influence the motion behavior of the robot that were extracted in the preceding exercise.
- To convert the relations obtained into fuzzy relations.
- To establish rules of generalization related to the relationship between variables that could affect robot motion.

Observation: A total of 15 pairs of relationships could be established.

Results:
90% of the students (72/80) got 14/15 correct relations.
90% of the students managed to correctly convert the relations into fuzzy relations.
80% of the students (64/80) could establish the correct rules derived from fuzzy relations.

Comments and interpretations:
Some 90% of the students got a good result because the analysis they had made in the first exercise was good. This result showed that if a good analysis is made first, the established relations result is also good. However, passing from relations expressed in fuzzy terms to rules expressed in textual terms became difficult for some students.

The final measurement again involved the cognitive variables: analysis, construction of relations and rules of generalization expressing stable and unstable robot motion.

Exercise: Interacting with the simulator to establish rules of generalization that can express stable and unstable robot motion.

Observation: The rules of generalization expressing stable and unstable robot motion depend on the analysis, constructions of relations and the rules of generalization affecting robot motion.

Results: 90% of the students could arrive at established rules that could determine if certain postures and their combination could affect the stability of the robot.

Comments and interpretation: Derived from the results obtained, we can infer the following rule: Good analysis → Good construction of relations → Good generation of rules to describe stable and unstable robot motion.

Behavior of simulated postures vs. the posture behavior of the real robot

The model is completely valid for the bipedal walking e-nuvo robot because it was abstracted from a visualization of the sequences of movements that the robot followed as motion files were downloaded from a PC. Through the simulator, it is shown that the model is based on real-life situations in which the robot goes through dancing or walking sequences and where each posture is extracted by fuzzy logic into generalization concepts that, one by one, define the quality of the posture. The movements executed by the robot are reflected in the simulator, meaning that the motion is the same. Since the model is applied to the simulator, and since the simulator is an extraction of the real robot, by observing the results reported above, we can conclude that the model is valid for the real bipedal walking robot that was worked with.

The advantage of this model is mainly that, due to the abstraction made into stability levels, an integration by concepts was obtained, which makes the sequence of movements executed by the robot easier to understand and analyze. Owing to the abstraction performed in a hierarchical tree mode, the insertion or deletion of relations among variables is left open, so that the general classification could be debugged to give a better approach to reality. In this way, during the classification process relations could be corrected or redefined, adding contributions to the model.

The model allows one to, through a process of modular hierarchic abstractions, easily interpret the sequences of movements in terms of stability so as to determine whether the robot will or will not fall.

CONCLUSION AND FUTURE WORK

The main objective of the simulator development was to motivate the students to develop/use simulators to understand difficult concepts. In addition, the research into alternative approaches has been encouraged for the same reason. For this, a model based on a fuzzy relations approach has been proposed. This allows an analysis based on symbolical variables instead of the numerical method of the classical approaches. The main purpose of this investigation was centered on studying the motion behavior of bipedal robots based on sequences of postures that represent walking or dancing routines.

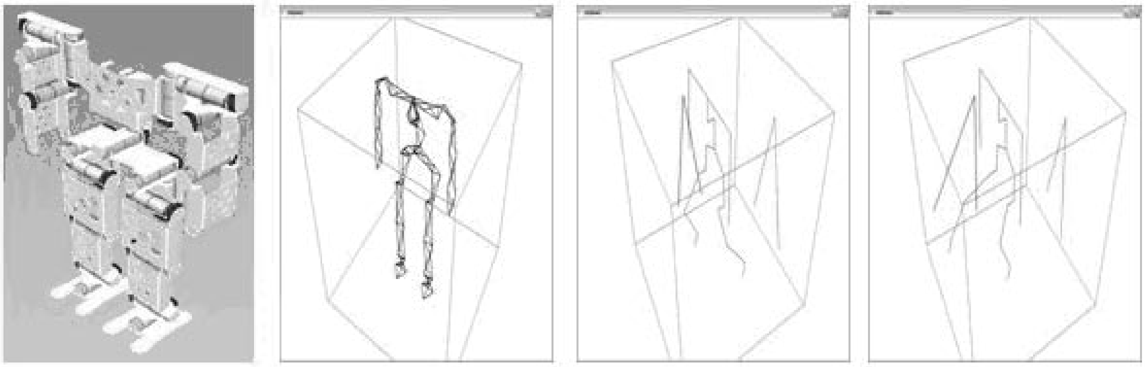

Fig. 8. The new version of the simulator currently being developed. The two final images in Fig. 8 show the vectors of legs projected onto X–Z and Y–Z planes.

Based on the analysis of results, almost 90% satisfaction was achieved, both for the understanding of the concept of motion behavior and for the cognitive aspects associated with the study.

Because of the transitive property of the fuzzy relations, the model could potentially be able to predict adequately different behaviors during motion sequences. However, there are certain limitations to be considered. The robot upon which this investigation was based was a 12-DOF-bipedal robot, so the model would only be correct for robots of this kind.

Finally, future research projects related to the subject could be devised in order to complete this model. One project could be the deduction of a general model for two-legged robots. A currently development is the 3D simulator of a humanoid robot. Part of this development is illustrated in Fig. 8.

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Fernando Ramos Quintana is a Senior Researcher at the Monterrey Institute of Technology (ITESM). He is the head of the Graduate School on Computer Science and Engineering at the Cuernavaca Campus. Dr. Ramos holds a Ph.D. degree in Robotics from the Institut de Productique Laboratoire de Automatique, Université de Franche Comté, Besancon, France, plus a Master's degree in Computer Science from Université Franche-Comté, Besancon, France, and a Bachelor's degree in Electronic Engineering from the Mexican National Polytechnic Institute. His research interests include robotics, multi-agent systems and decision support systems. He is a member of the Mexican Council for Science and Technology, Level 1.

Enrique David Espinosa is an Associate Professor of Computer Science at the Monterrey Institute of Technology (ITESM). He holds Ph.D. and Master of Science degrees from ITESM, and a Bachelor of Science from the University of Kansas. He is a member of the Mexican Council for Science and Technology, Level 1. His research interests include multi-agent systems, service oriented architectures and enterprise computing.

Sandra López, **José CarlosRebón**, **Alejandro Hernández** and **Abel Arredondo** are graduate students at the Tecnológico de Monterrey, Campus Cuernavaca.