Head stabilization based on a feedback error learning in a humanoid robot

Conference Paper · September 2012

DOI: 10.1109/ROMAN.2012.6343793

Head stabilization based on a feedback error learning in a humanoid robot

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***Abstract*— In this work we propose an adaptive model for the head stabilization based on a feedback error learning (FEL). This model is capable to overcome the delays caused by the head motor system and adapts itself to the dynamics of the head motion. It has been designed to track an arbitrary reference orientation for the head in space and reject the disturbance caused by trunk motion. For efficient error learning we use the recursive least square algorithm (RLS), a Newton-like method which guarantees very fast convergence. Moreover, we implement a neural network to compute the rotational part of the head inverse kinematics. Verification of the proposed control is conducted through experiments with Matlab SIMULINK and a humanoid robot SABIAN.**

I. INTRODUCTION

Recent neurophysiological studies suggest that the head-fixed reference frame in humans plays a major role in body motion planning and execution [1]. It seems to be the privileged reference system where all sensory information is integrated and where whole-body motion planning occurs. This is one of the key concepts of "The Sense of Movement" [2] and that could simplify significantly motion planning and execution in complex kinematic structures like humans.

In humans, the vestibular system, perceiving rotational velocities and linear accelerations, provides perception information of the head movements and postures relative to space and gravity. It provides proprioceptive signals for the sense of movement. The central nervous system uses this information to generate a unified inertial reference frame, centered in the head that allows whole-body coordinated movements and head-oriented locomotion [2].

Pozzo and colleagues were the first to study the head behavior during locomotion [1]. Their experimentation revealed that vertical translation of the head is not stabilized to zero during human walking. The head always rotates in the opposite direction from head translation along the vertical axis. Hirasaki and colleagues [3] showed that the head oscillates up and down from about 4 centimeters during slow walking (0.8 m/s) to about 10 in fast walking (2 m/s) and about 5 centimeters from left to right in average in walking speeds between 1.4 and 1.8 m/s. A compensating contribution of the head yaw allows counteracting for body yaw. The same behavior has been observed for the roll and the pitch rotation of the head [4].

Walk with direction changes has been examined in [4]. Turning movements of both small radius (50 cm) and large radius (200 cm) have been captured at various speeds. One of the findings of this research is that large radius turns are in fact a combination of small radius turns and straight walking. So it is sufficient to analyze and replicate, in addition to straight walking treated in the previous section, small-radius turning. Considering small-radius turns, the main behaviors which are not present during straight walking and should be replicated are the yaw anticipation and roll anticipation. Analyzing the yaw data during turn, Imai in his work [4] shows that head yaw is controlled (as it follows a smoother trajectory than body yaw) but it is not stabilized around trajectory (heading) yaw as we could expect. Head yaw seems to anticipate heading and body yaw. In other words, subjects tend to turn their head towards the direction of the turn before the turn actually begins. This kind of behavior is not generated by a feedback mechanism as it begins before the turn actually takes place. The roll is not stabilized to zero as it is during straight walking. There is an anticipatory component of roll in the direction of the turn (i.e. the head tilts towards the inside of the turning trajectory). The magnitude of this behavior, called roll anticipation, is not negligible: maximum roll is about 8° and there is a sustained roll component of approximately 5° during the most part of

This study was supported in part by the by RoboSoM project from the European FP7 program (grant agreement No. 248366.

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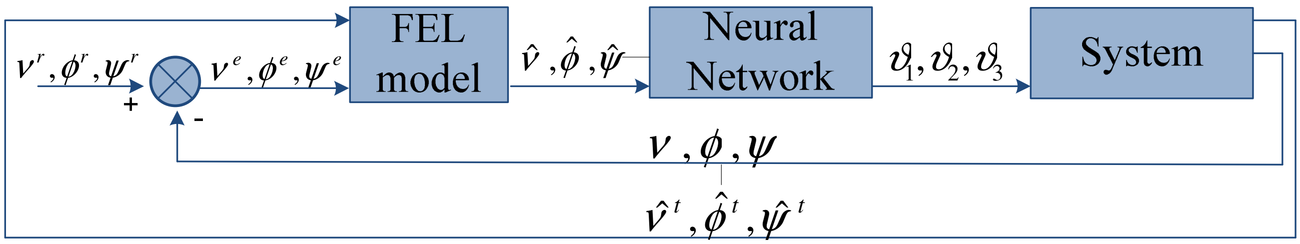

Fig. 1. Adaptive Head Stabilization model.

the turn [4]. This behavior, moving the head towards the interior of the curve, creates a stabilizing moment about the feet which helps maintaining balance during the turn (counteracting the outward weight shift caused by centrifugal force).

Considering this analysis, we can conclude that in order to replicate head movement behaviors found in human walk it is necessary and sufficient to be able to control the orientation (roll, pitch and yaw) of the head in space. The described behaviors can be replicated by giving suitable references to the head orientation. A bio-inspired model [5], based on these principles, has been proposed. It considers the trunk rotation as a disturbance and allows following an input reference head rotation, compensating the trunk rotation.

From the robotic point of view there are some implementations of head stabilization model [6, 7, 8]. Yamada and colleagues [6] propose a method for the stabilization of the snake-like robot head based on the neck control. The aim of their controller is to reject the disturbance of the body on the head using a continuous model. Another work on the head stabilization implementation on a robotic platform is proposed by Santos and colleagues [8]. This work focuses on a controller which minimizes the head motion induced by locomotion. In particular, the head movement is stabilized using Central Pattern Generator and a genetic algorithm. The results on a Sony AIBO robotic platform show the head movement is not totally eliminated during locomotion. Another controller [7] for the head stabilization has been implemented on the Sony AIBO robot. This controller is based on a machine learning algorithm able to learn the compensation for the head movements when no stabilization mechanism is present.

In this work we propose an adaptive model based on a feedback error learning (FEL) [9] [10]. This model is capable to overcome the delays caused by the head motor system and adapts itself to the dynamics of the head motion. It has been designed to track an arbitrary reference orientation for the head in space and reject the disturbance caused by trunk motion. For efficient error learning we use the recursive least square algorithm (RLS), a Newton-like method which guarantees very fast convergence . Moreover, we implement a neural network to compute the rotational part of the head inverse kinematics.

The paper is organized as follows: in the next section we describe the model of head stabilization. In third section we present the implementation in Matlab SIMULINK. In following section we describe the robotic platform and results of the experiments. Section VI provides conclusions and future work.

II. A Model for Head Stabilization

The control of the head rotation during walking appears essential in order to keep a stable head centered reference frame. In this perspective, a model in which the head is stabilized is proposed. The model we propose considers the trunk rotation as a disturbance and allows following an input reference head rotation, compensating the trunk rotation.

Three frames of reference are considered for the model: 1) the world reference frame O – xyz; 2) and the head frame, fixed to the head, 3) and the trunk frame, fixed to the trunk. The head frame is composed by a rotation matrix ${}^W_H\mathrm{R}$ which describes the orientation of the head with respect to the world frame as well as by a matrix ${}^T_H\mathrm{R}$ which describes the orientation of the head with respect to the trunk. The trunk frame orientation is composed by a rotation matrix ${}^W_T\mathrm{R}$ which describes the orientation of the trunk with respect to the world frame. In this model, the matrix ${}^W_T\mathrm{R}$ depends on the motion during walking and can be considered as an external disturbance.

A controller using as feedback the actual absolute RPY angles of the head (ν,ϕ,ψ),was designed to track an arbitrary reference orientation in space (not relative to the trunk) using Roll, Pitch and Yaw angles (Fig 1). The controller is able to follow a reference orientation (ν^r, ϕ^r, ψ^r) spanning in the whole workspace of the head and reject the disturbance caused by trunk motion.

In order to obtain information about trunk motion, we can notice that, knowing the absolute orientation of the head ${}^W_H\mathrm{R}$ and the orientation relative to the trunk ${}^T_H\mathrm{R}$ we could estimate the rotation of the trunk,

$$ {}^W_T\mathrm{R} = {}^W_H\mathrm{R}({}^T_H\mathrm{R})^{-1} \quad (1) $$

and then, by differentiation, we could obtain the time derivatives of the trunk RPY angles which can be used to compute the estimation of trunk orientation angles $\hat{\nu}^t$,$\hat{\phi}^t$, $\hat{\psi}^t$ and their derivatives $\dot{\hat{\nu}}^t$, $\dot{\hat{\phi}}^t$, $\dot{\hat{\psi}}^t$.

The controller we propose is based on a feedback error learning model. This model estimates the orientation of the head $\hat{\nu}$,$\hat{\phi}$,$\hat{\psi}$ which allow following the reference orientation (ν^r, ϕ^r, ψ^r). The output of this model is sent as input to a Neural Network which computes the joint positions relative to the estimated orientation.

A. *Neural Network*

In the case of the head it has been possible to derive a closed-form solution to the rotational part of the inverse kinematics problem, but in general this is not possible for all robotics manipulators. Even in the cases where this is possible, the expression can be too complicated and computationally heavy to calculate explicitly, and multiple solutions could be present. We would like to find an Artificial Neural Network capable of solving the inverse kinematics problem without using the closed form solution.
This network takes as input the desired the desired head orientation angles (RPY) and it yields as output the joint angles which realize that RPY triple in the absence of torso motion (${}^{W}_{H}R = {}^{T}_{H}R$). We decided to use this solution instead then directly compute the closed form for the kinematics the head stabilizer "platform independent". For this purpose we implemented a feedforward network has been implemented to learn and perform the head inverse kinematics.
The network has one hidden layer of 20 units. It takes as input the head orientation (ν,ϕ,ψ) and as output the neck joints angles ($\theta 1$, $\theta 2$, $\theta 3$).

B. *FEL Model*

The learning controller takes as input the trunk orientation, its derivative and the orientation error. We replicate this model for each orientation (roll, pitch and yaw). In Fig.2 we show the FEL model schema relative to the yaw. FEL employs an appropriate way of mapping sensory errors into motor errors [10].
As a computationally efficient learning mechanism, we use the recursive least squares (RLS) [11] for the "Learning Network", introducing a small modification in the standard RLS algorithm. In the following, x is the state vector containing the angular position of the trunk (roll, pitch or yaw) and its derivative.
To predict the angular position the model uses a second order linear system. The recursive least squares algorithm (RLS) is employed for learning, because it is robust and it guarantees convergence. The algorithm (for the yaw rotation) is as follows:

$$P(t) = \frac{1}{\lambda}\left[P(t-1) - \frac{P(t-1)x(t)x(t)^{T}P(t-1)}{\lambda + x(t)^{T}P(t-1)x(t)}\right] \quad (2)$$

$$w(t) = w(t-1) + \frac{P(t)x(t)}{\lambda + x(t)^{T}P(t)x(t)}\psi^{e}(t+1) \quad (3)$$

$$\hat{\psi}(t) = w(t)^{T}x(t) \quad (4)$$

Where P is the inverted covariance matrix of the input data, and λ is the forgetting factor which lies in the [0, 1] interval. For $\lambda = 1$, no forgetting takes place, while for smaller values, the oldest values in the matrix P are exponentially forgotten. Essentially, the forgetting factor ensures that the prediction of RLS is only based on $1/(1-\lambda)$ data points.

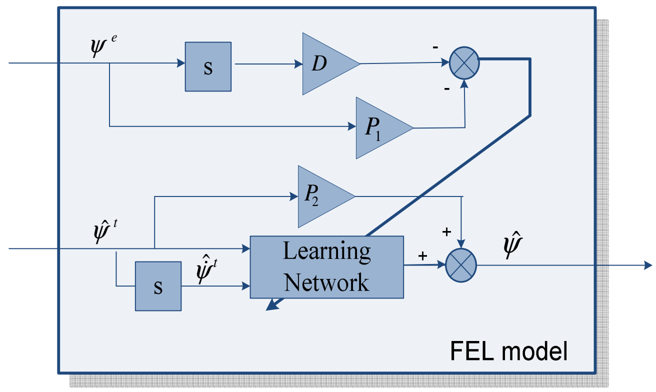

Fig.2. FEL model to control yaw angular rotation.

III. SABIAN ROBOT

SABIAN (Sant'Anna BIped humANoid) is a biped humanoid robot developed by the Robot-An Laboratory, at Scuola Superiore Sant'Anna. It is a copy of WABIAN (WAseda BIped humANoid), [12]. Compared to most bipedal humanoid robots, which walk with bent knees, WABIAN is able to perform a human-like walking, with stretched knees, and to get the pelvis motion, raising the hip. WABIAN (Fig 3) is approximately the size of the average adult Japanese women (1.5m in height, and 64kg in weight). The SABIAN robot (Fig 3) has 7 DOF in each leg, 2 DOF in the waist, which help the robot perform stretched knee walking, 2 DOF in the trunk. Every degree of freedom has a bio-inspired range of motion, defined in reference to human motion measurements. In order to reach the objectives of a visuo-guided locomotion, the iCub head [13] has been mounted on the SABIAN platform. The iCub head contains a total of 6 DOFs: 3 for the neck (pan, tilt and swing) and 3 for the eyes (an independent pan for each eye and a common tilt). The visual stereo system consists of 2 dragonfly2 cameras with a maximal resolution of 640X480 pixels. All the joints are actuated by DC servo motors with relative encoders. The processing unit consists of a PC104 with a live Debian distro running on it. An IMU (Inertial Measurement Unit) is mounted on the iCub head. The IMU sensor is an XSense MTx unit. It has an angular resolution (3) of 0.05° with a repeatability of 0.2°. The roll and pitch static accuracy is 0.5° while the dynamic one is 2°. The IMU sensory data are sampled with a 100Hz frequency. The YARP system [14] (a set of libraries, protocols, and tools to keep modules and devices cleanly decoupled) is used to distribute the head control.

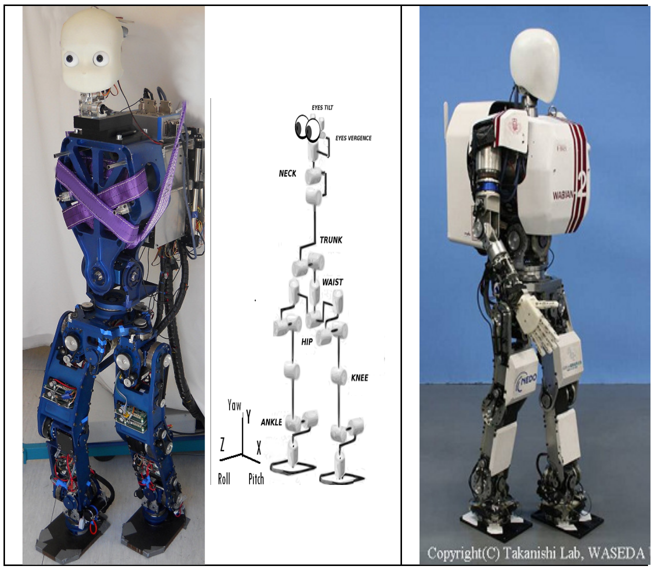

Fig. 3. SABIAN humanoid platform (left), head and body kinematics of the SABIAN (middle) and the WABIAN humanoid robot (right)

IV. RESULTS

A. *Simulation in Matlab SIMULINK*

All the simulation experiments start from scratch, i.e. with all initial states including the weights of the learning system set to zero. The FEL model has been trained on sinusoidal motions with the following dynamics:

$$x(t) = A * \sin(\omega * t) \qquad (5)$$

where x(t) is the trunk roll, pitch or yaw orientation (expressed in degrees) at the time t and A is the amplitude of the dynamics. The frequency (ω) has been tested between 0.1 Hz and 1.5 Hz. Moreover the model has been tested with amplitude between 5 and 20 degree with a 1-degree step for each orientation. The control loop runs at 100 Hz, the same frequency of the IMU data. The IMU has been modelled as zero-mean white noise (disregarding drifts which should be eliminated by the integrated Kalman filter of the inertial unit). For the implementation we used these parameters: P1 = 0.1, P2 = 0.1, D = 0.01, $\lambda = 0.98$. We simulated the direct kinematics of the SABIAN robot head (3 DoFs).

In order to assess how this controller behaves considering realistic actuation limits an approximate dynamic simulator has been developed. The model simulates the dynamics of the SABIAN head, disregarding the inertial forces given by the torso motion (which, opposing torso motion, actually help stabilization). The dynamic parameters of the links are calculated considering the head a homogeneous sphere of radius equal to 6 cm and weight of 1.5 kg (estimated from [10]). The weight of the first two links is considered as 0.1 kg and their inertia tensor as negligible (10^{-4} kg m^2). The robot dynamics simulator has been implemented in Simulink with the Robotics Toolbox, and fully simulates the robot dynamic equation. Gravity has been turned off during the simulation as is considered feed-forward compensated by the low-level controllers. The torques required to compensate gravity are very low for small angles (in the order of 0.08 Nm for 5°) and will be neglected.

Figures 4,5 show the results of the Adaptive Head Stabilization model simulation for pitch, roll, and yaw. Each graph contains the trunk rotation which has a sinusoidal motion, the predicted value of the RLS algorithm and the rotation error of the system. We consider the rotation error of the system (ν^e, ϕ^e, ψ^e) the difference between the reference head rotation and the head rotation (for roll, pitch and yaw).

The head orientation reference was constant and equal to 0 for all three angles in all the simulations.

For the three rotational axes the peak-to-peak amplitude of the error after 5 seconds is less than 0.6 degrees.

Figure 7 shows the convergence of the RLS regression parameter in the same test for the yaw rotation. They reach convergence after 16 seconds. We consider that the regression parameters stabilize when the peak-to-peak amplitude of the last 5 seconds is less than 0.1 for both parameters of roll, pitch and yaw.

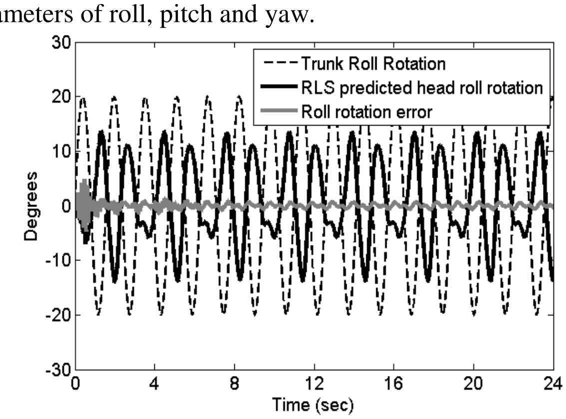

Fig. 4. Results of the Adaptive Head Stabilization model relative to the roll rotation

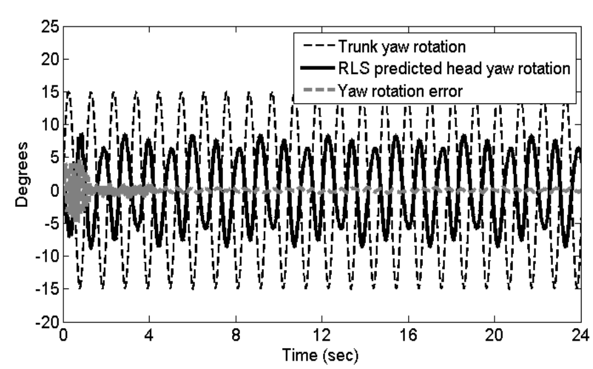

Fig. 5. Results of the Adaptive Hea d Stabilization model relative to the yaw rotation

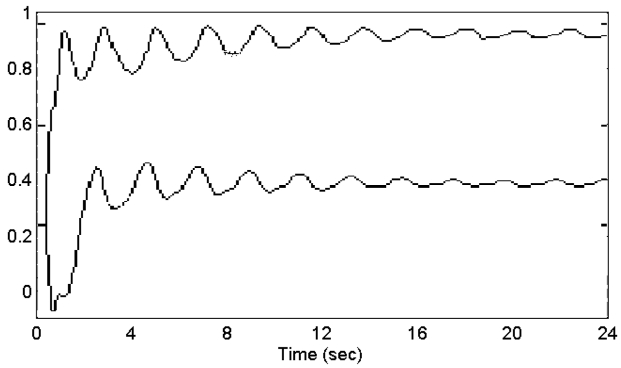

Fig. 6. Regression parameters convergence in the FEL model relative to the yaw rotation

B. Neural Network Results

In preliminary studies, the network was tested in a simulated environment (Matlab SIMULINK). A 7000 element random dataset, obtained using the direct kinematics, was used to train the network. The dataset was divided in training (70%), validation (15%) and test set (15%). To create the dataset, we considered 7000 random joint positions and for each of them the direct kinematics was calculated. The set of head orientations obtained became the network inputs, whereas the jonts positions became the outputs. After 600 epochs, the test error was 0.0373 degrees.

For the robot experiment the dataset was calculated using the IMU sensor of the iCub head. During an initial calibration sequence, the head was randomly moved, to create a dataset <IMU orientation, encoder position> of 7000 elements. This dataset (70% training-set, 15% validation-set, 15% test-set) is used to train the network, obtaining a test-set mean square error of 0.6 degrees in 2 minutes (358 epochs).

C. Results of the model implementation in the SABIAN robotic platform

We performed two kinds of tests on the SABIAN robot. In the first test the robot was suspended on the lift and moved by the author to deviate body from the vertical orientation (figure 8). In the second test the robot performed a 45 step walking that follow a right curved trajectory (figure 11). We chose this task because it involved straight and curved steps. In both of the experiments the roll and pitch stabilization were active together. The head orientation reference was constant and equal to 0 for the two angles (roll and pitch). In figure 9 and 10 we present the results (respectively roll and pitch) of the implementation on the SABIAN robot during a "shaking" experiment. Worth of notice is that, in the two rotational axes, the pitch and the roll rotation error are less than 2 degrees, while the trunk peak-to-peak amplitude was almost 15 degrees for the pitch and 8 for the roll. The oscillations frequency was about 1 Hz.

Fig. 7. Five snapshots of the robot head during a shaking movement in the horizontal plane. The controller allows to keep stable the head orientation

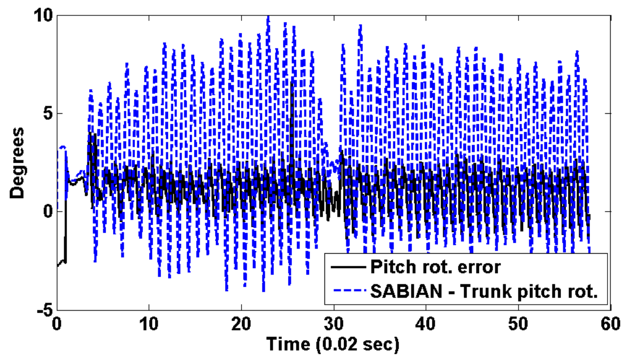

Fig 8 Results on the SABIAN robot of the implementation of the Head stabilization model during a "shaking"test relative to the pitch rotation

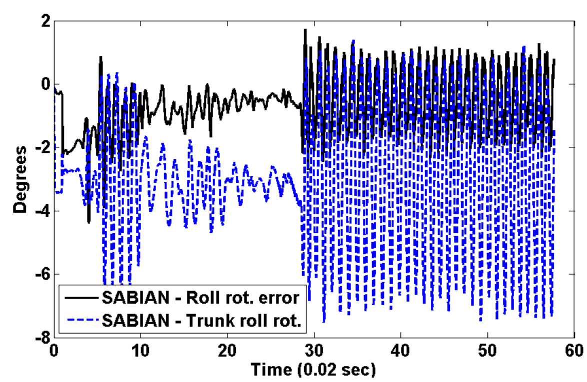

Fig 9 Results on the SABIAN robot of the implementation of the Head stabilization model during a "shaking"test relative to the roll rotation

We also tested the head stabilization controller during walking. This experiment started with the network weights and the regressor parameters of the FEL set to the values reached at the end of the training phases. For the training phase the robot performed eight steps in a straight line and eight steps to follow a curved path. Results show the head is stabilized compared to the trunk motion. Figure 10 shows the results relative to the pitch. The peak to peak amplitude of the head is less than 2 degrees during the whole pattern execution.

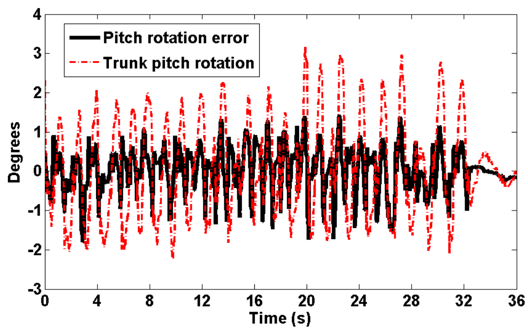

Fig 10 Results on the SABIAN robot of the implementation of the Head stabilization model during walking relative to the pitch rotation

V. Conclusion

In the paper we presented an adaptive controller which is able to stabilize the head rotation. The implementation of the algorithm was done in Matlab SIMULINK and preliminary experiments have been carried out in the robotic platform. The model is able to follow a reference orientation for the head rejecting the trunk disturbance. Moreover this model, based on a FEL model, is capable to overcome the delays caused by the head motor system and adapts itself to the dynamics of the head motion. Results of the simulation on Matlab SIMULINK and results on the robotic platform show significant improvement in stability of the head.

Moreover we plan to evaluate the influence of the head stabilization on the stability of the visual image acquired from the on-board cameras and resultant simplification of the visual reconstruction of the environment.

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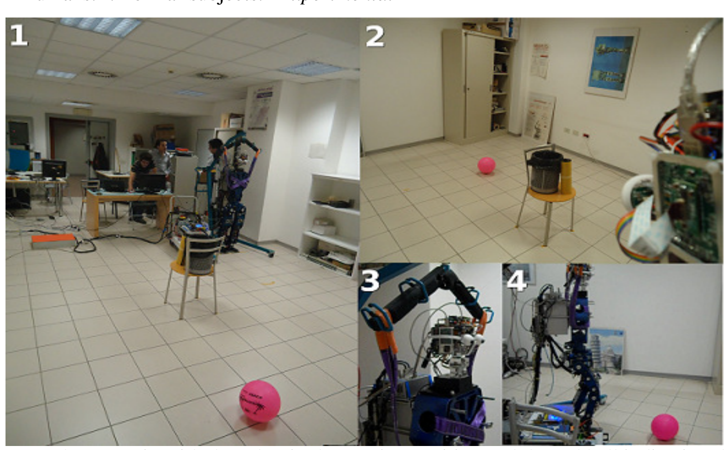

Fig. 11. Walking test. 1 The scenario with the robot in the starting position and the red ball indicating the end of the path. 2 The scenario from the robot point of view. 3 / 4 The robot performing the walking pattern with head stabilization.