Learning to Stabilize the Head of a Walking Quadrupedal Robot Using a Bio-Inspired Artificial Vestibular System

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Abstract—**During quadrupedal robot locomotion, there is pitch, yaw, and roll of the head and body due to the stepping. The head motion adversely affects visual sensors embedded in the robots head. Mammals stabilize the head using a vestibulo-collic reflex that detects linear and rotational acceleration. In this paper we describe the use of a machine learning algorithm that utilizes signals from an artificial vestibular system that has been embedded in the robot's head. Our approach can rapidly learn to compensate for the head movements that appear when no stabilization mechanism is present. The stabilization using a Sony Aibo robot occurs in only a few gait cycles.**

I.INTRODUCTION

Robot locomotion has been studied using a wide range of wheeled and legged robots. Although wheeled robots move quickly, they lack the versatility of legged robots. As a result, there has been a concerted effort within the robotics community to understand the motion of legged robots. The motion of the biped and quadrupedal robots, however, generates considerable pitch, roll, and yaw body and head movements as the robot steps during locomotion, causing cameras mounted on them to also pitch, yaw, and roll [1]. The very fact that legged motion generates this kind of disturbance makes it difficult to keep the visual frame stable and creates problems when vision information is used as a major source of sensory data for the robot.

To counter the effects of legged robot motion on visual acquisition, a number of mechanisms have been implemented for legged robot gait. One approach has used feedback from sensors attached to the motors that drive the head with the aim of compensating the change of motor angles [2]. A second approach estimated head motion and tracked objects in the visual frame using a Kalman filter [2]. These implementations do not generate accurate representations of head motion in space, resulting in considerable errors during tasks that make use of visual information, such as self-localization [3], navigation [4] and target identification [5]. This, in turn, leads to non-optimal trajectories in adjusting robot motion towards the target.

Other methodologies have utilized feedback from motors that drive the robot head to learn and determine the actual head motion during walking. These learned responses are used to then move the head to compensate for any motion. Such approaches were based on the model-based method introduced in [6]. Still other methods have been developed, which learn head movement as an elliptical locus during gait [8]. While some improvement in stability of the head can be achieved using no additional information, the most successful of these approaches uses an inertial sensor along with optical flow in its visual frame to detect the movement of a head to help stabilization vision [7]. This work has concentrated on movement of the head as input and cameras were driven by a neural network to compensate for the head rotation about a vertical axis [7]. This work was limited to rotations about a vertical axis and linear motion along the horizontal axis.

The purpose of the study reported here as to investigate the use of an inertial sensor, which mimics the vestibular apparatus in mammals, combined with learning algorithms to stabilize the head during locomotion. The hypothesis is that stabilization of the head could be significantly improved if we make use of data on head rotations and linear accelerations when the robot walks. In our approach, the sensor information utilizes rotation and translation in three dimensions to emulate the robot's behavior during locomotion. We have therefore implemented a compensatory mechanism that would tend to stabilize the head in three dimensions. The implementation uses an artificial vestibular system, which we have recently

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embedded into the head of a Sony Aibo quadrupedal robot [1]. The present work extends this by utilizing methods of machine learning to adapt head motion using sensor information about head rotation in three dimensions. We have also shown how the system might learn to improve its compensatory ability using the cyclic gait to overcome the delays in head movement control. The results indicate that head stabilization can be learned rapidly in real time as the robot is walking.

II. Primate Vestibular Syshtem

In primates, the vestibular system is a biological acceleration sensor, which is embedded in the inner ears on both sides of the head, providing information about head movement in space [9]. This information is then utilized to stabilize gaze and orientation during locomotion in primates [10, 11].

The primate vestibular system consists of two organs namely semi circular canals (anterior, posterior and horizontal) and otoliths (utricle and saccule) (Fig. 1A).

A B

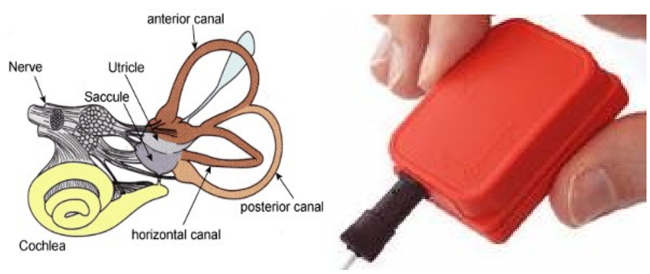

Fig. 1. (A) Human Vestibular System: The three semi-circular canals -anterior, posterior and lateral (horizontal) canals and the otoliths (utricle and saccule). (B) Artificial Vestibular System: MTx acceleration sensor. Outputs are calibrated 3D rate of turn, and 3D linear acceleration.

The semicircular canals sense angular acceleration through a set of approximately orthogonal fluid-filled canals (Fig. 1A) (endolymph), which are blocked by a membrane called the cupula. When the head rotates, the fluid pushes against the cupula activating hair cells that transmit the signal about head movement [9]. The viscosity of the fluid and the elastic properties of the cupula determine the dynamics of how the head movement is transduced by this canal system. The inertial properties of the fluid are relatively minor.

The semicircular canals in primates are activated by angular acceleration. However, due to the dynamical properties of the canals, the angular acceleration is integrated and generates an angular velocity for frequencies above approximately 0.04 Hz. Therefore, the signal coming from the canals is related to angular velocity over the frequencies considered in this study. The inertial sensor in the human vestibular system (Fig. 1) does in fact output signals related to angular velocity, which activates both ocular and neck reflexes (vestibulo-ocular reflex (VOR) and vestibule-collic reflex (VCR)). The otoliths, which sense linear acceleration, accomplish this by activating hair cells that are embedded in membrane containing crystals.

The neck reflexes based on these sensors have been classified into an angular vestibulo-collic reflexes (aVCR) and linear vestibulo-collic reflexes (lVCR). The aVCR (rotation) generates head movements incrementally for changes in head rotation to maintain stable gaze. The lVCR (translation) rotates the head to maintain fixation on a particular point in space. A similar mechanism, the vestibulo-ocular reflex, stabilizes the eyes to compensate for the head movement and generates gaze stability. In this paper, we only concentrate on the aVCR. We explore the implementation of the vestibulo-ocular reflex in [12].

III. Design of Artificial Vestibular System and Sensing of Head Motion

The key to our construction of an artificial vestibular system is the use of an intertial sensor, mounted in the head of the robot, which substitutes for the semi-circular canals described above. The sensor we use is the *MTx Sensor* by XSENS® Motion Technologies. This is a complete inertial measurement unit capable of providing 3D linear acceleration, 3D rate of turn and 3D magnetic field data (Fig. 1B). Static accuracy for Roll/Pitch is <0.5^0 and for heading (yaw) is <1.0^0. Dynamic accuracy is 2^0 RMS and angular resolution is 0.05^0. The sensor is configured to send information at 125Hz.

The orientation coordinate system of the MTx sensor has a fixed coordinate frame with its X-axis pointing to the local earth's magnetic north (Field). The Y-axis follows the right handed coordinate system pointing to the west of the X-axis and the Z-axis completes the right handed coordinate system, pointing up as shown in Fig. 2. The sensor fixed coordinate system is a right-handed coordinate system. The output is factory calibrated with sensor frame relative to the earth fixed frame.

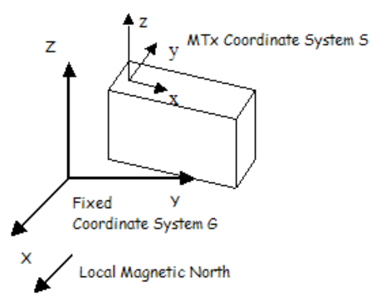

Fig. 2. Earth-Fixed Coordinate frame and Acceleration Sensor Coordinate frame

A. Connecting the sensor to the robot

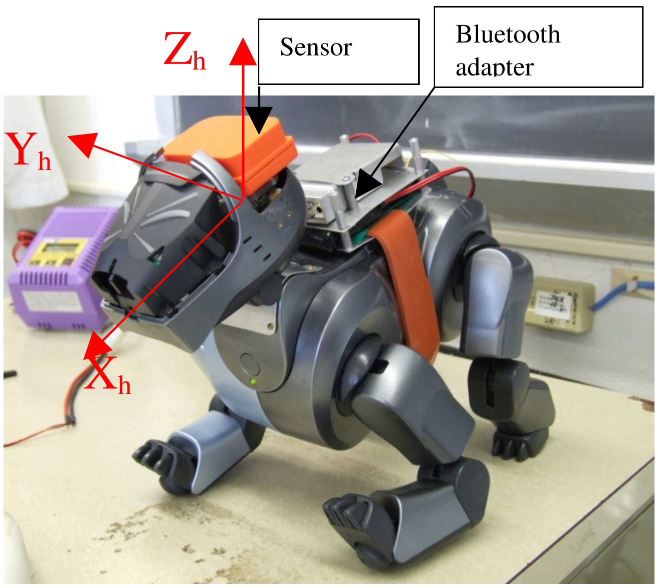

Fig. 3. The Sony Aibo robot with the XSENS sensor mounted firmly in the head. The Bluetooth adapter along with its batteries can be seen strapped to the back. The head coordinate system is shown.

The robot that we have augmented with this sensor is a Sony Aibo ERS-210 robot. The ERS-210 is a quadrupedal robot that has three perpendicular degrees of freedom (DOF) in the head. The three degrees of freedom makes it possible to study the 3D head motion in space. The Aibo is a closed platform and can only be interfaced using a wireless 802.11b network. For this reason, the sensor is connected to a host computer instead, using a serial connection tunnelled through wireless Bluetooth adapters. Signal processing is done on the host computer and any compensatory commands or trajectories are sent to the robot through a wireless network using the TCP/IP protocol.

B. Implementation of Compensatory mechanisms

The head moves in space relative to a coordinate frame defined by $X_hY_hZ_h$ (Fig. 3). The naso-occipital axis (X_h), the interaural axis (Y_h) and the axis out of the top of the head (Z_h) form a right-handed coordinate frame for the head. The inertial sensor is embedded in the head approximating in the location of the vestibular system in primates and is aligned with the head coordinate frame. The head motors represent a gimbal system according to a Fick convention. The movements of the head are programmed to rotate in a compensatory fashion based on rotational velocity information obtained from the sensor. It therefore mimics the high frequency angular VOR of the primate [9] and is implemented as follows [13]:

Rotations of the robot head can be given as a sequence of rotation matrices given by:

$$R_{PYR}(\theta,\phi,\psi) = R_X R_Z R_Y \tag{1}$$

where

$$R_x(\psi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\psi & -\sin\psi \\ 0 & \sin\psi & \cos\psi \end{bmatrix} \quad R_y(\theta) = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \quad R_z(\phi) = \begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

Substituting Eqn. 2 into Eqn. 1, we obtain the rotation matrix for the head relative to the body as:

$$R_{PYR} = \begin{bmatrix} \cos(\phi)\cos(\theta) & -\sin(\phi) & \cos(\phi)\sin(\theta) \\ \cos(\psi)\sin(\phi)\cos(\theta)+\sin(\psi)\sin(\theta) & \cos(\psi)\cos(\phi) & \cos(\psi)\sin(\phi)\sin(\theta)-\sin(\psi)\cos(\theta) \\ \cos(\psi)\sin(\phi)\cos(\theta)-\cos(\psi)\sin(\theta) & \sin(\psi)\cos(\phi) & \cos(\psi)\sin(\phi)\sin(\theta)+\cos(\phi)\cos(\theta) \end{bmatrix} \tag{3}$$

The incremental change in head rotation is obtained from the inertial sensor as the angular velocity vector represented by ω, in rad/sec. The incremental axis of rotation of the head at any given time t is therefore given by

$$\hat{\nu} = \frac{\omega}{\|\omega\|} \tag{4}$$

where $\hat{n}$ is a unit vector in the direction of the incremental rotation.

Φ_{Inc} is the incremental angle of rotation about the axis of rotation and is given by:

$$\Phi_{Inc} = \|\omega\|\,\Delta t \tag{5}$$

where Δt is the time (8mS) between the two sensor readings.

The resulting incremental axis of rotation and incremental angle of rotation is fed into the Rodrigues Formula (An efficient method to compute rotations) [14].

$$R_{Inc} = \begin{bmatrix} \cos\Phi + n_1^2(1-\cos\Phi) & n_1 n_2(1-\cos\Phi) - n_3\sin\Phi & n_1 n_3(1-\cos\Phi) + n_2\sin\Phi \\ n_2 n_1(1-\cos\Phi) + n_3\sin\Phi & \cos\Phi + n_2^2(1-\cos\Phi) & n_2 n_3(1-\cos\Phi) - n_1\sin\Phi \\ n_3 n_1(1-\cos\Phi) - n_2\sin\Phi & n_3 n_2(1-\cos\Phi) + n_1\sin\Phi & \cos\Phi + n_3^2(1-\cos\Phi) \end{bmatrix} \tag{6}$$

Eqn. 6 provides the incremental rotational matrix representing the change in angles of the head in 3 dimensions.

The new position of the servomotors at any instant of time is obtained by applying the incremental rotation to the current rotation matrix representing the current motor positions:

$$R_{new} = R_{inc}(\nu_S)\,R_{PYR}(\theta_{old},\phi_{old},\psi_{old}) \tag{7}$$

And then extracting the individual motor position:

$$\begin{aligned} \psi_{new} &= \tan^{-1}\frac{r_{32}}{r_{22}} \\ \theta_{new} &= \tan^{-1}\frac{r_{13}}{r_{11}} \\ \phi_{new} &= -\sin^{-1} r_{12} \end{aligned} \tag{8}$$

where the parameters r_{11}, r_{12}, r_{13}, r_{22}, r_{32} are the associated matrix elements for a particular head orientation in Eqn. (3). The change in position due to the incremental rotation may then be represented as:

$$\begin{aligned} \psi_{change} &= \psi_{new} - \psi_{old} \\ \theta_{change} &= \theta_{new} - \theta_{old} \\ \phi_{change} &= \phi_{new} - \phi_{old} \end{aligned} \tag{9}$$

The change in position in terms of joint angles may now be used to compensate the undesirable motion of the head.

IV. Limitations of the System

One factor which impacts the performance of the mammalian vestibular system is the response time of the system. Eye movements respond to a vestibular stimulus in less than 8ms, and this allows them to respond at frequencies up to 15-20 Hz. The head has greater inertia and responds up to frequencies of up to 2-3 Hz. Equally, robot performance in stabilizing the head will be limited by the motor and head response dynamics as in mammals. We performed a test to see how fast the robot's motors react to input and found that there is a delay of approximately 80ms between when a signal is sent to the motors and when a reaction can be seen. Wireless communication from the host computer and slow motors of the Aibo robot are the causes of the delay. This delay makes immediate compensation based on sensor output impossible on the Aibo robot.

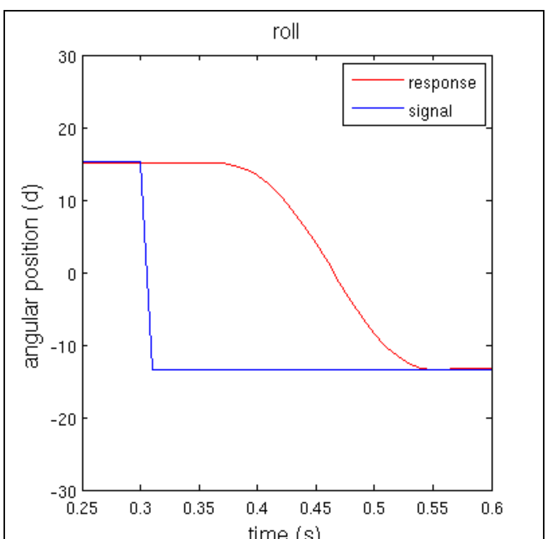

Fig. 4. The response time of the roll motor given input from the host. There is a delay of 80ms in starting the motion and the change of 30 degrees is completed in 250ms.

Fortunately the fact that gaits are cyclical allows us to synchronize the sensor output to cyclical trajectories and modify these trajectories in such a way that the motion is compensated for in future cycles. Thus, while we are unable to compensate for head motion immediately, the robot can use the information from the inertial sensor to *learn* how to compensate for head motion. If we can learn quickly enough, over just a few leg cycles, then we can still obtain good performance.

A. Controlling the robot through trajectories

The robot moves by following trajectories for all of its joints. A gait is defined by a trajectory for the leg joints T_{legs} and a trajectory for the head T_{head}. The trajectory is sampled at 8ms and cycle period is defined by the number of trajectory points times the sampling rate. Each point represents a position to move to for the set of motors.

1) Controlling the motion of the legs

The host software that processes the sensor signal includes a module for designing and modifying gaits in real time. The gaits may be hand tuned while the robot is moving and any updates are wirelessly sent to the robot. This allows us to quickly develop and adjust gaits for different terrain. Trajectories are created separately for the front and rear legs and are mirrored for the left and right legs. A sample gait used for this work may be seen in Fig.5.

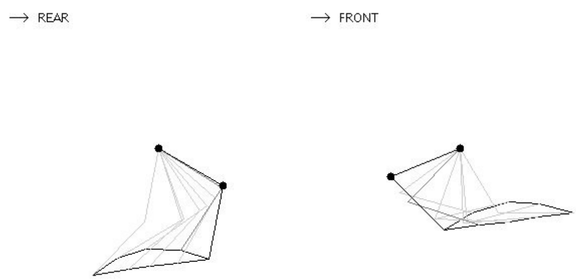

Fig. 5. Paths of the front and rear legs during a hand tuned walk.

2) Controlling the motion of the head

The head trajectories are the same length as the leg trajectories they correspond to and consist of three components for the pitch, yaw, and roll joints. These trajectories are learned by a mechanism described further in this paper.

B. Synchronizing the sensor

The sensor is synchronized to the robot trajectories by having both the robot and the host computer run a clock that represents the current point in the trajectory that is updated every 8ms. To synchronize, a sine wave is sent to the robot as its head trajectory. As the robot moves, the signal is detected by the sensor. The phase is updated on the host computer so that the start point of the trajectory sent to the robot matches the start point of the trajectory detected by the host.

V. Learning to Stabilize the Head

The artificial vestibular sensor provides information about how the head moves in space while walking. This information may be used to make compensatory movements to stabilize the head. The motion of the head as detected by the sensor can be thought of as the error that we want to remove. To remove this error, the robot needs to move in the opposite direction and we do this using a simple gradient descent method.

Let HT be the head trajectory with subcomponents HT_{pitch}, HT_{yaw}, and HT_{roll}. The trajectory for the iteration HT_0 represents keeping the head stationary at the zero position. $HT_0(i) = 0$ for all point i=0,1,…,n where n is the length of the trajectory. As the robot walks the motion caused by walking is detected by the sensor as described in section III.B. This motion represents the error, e, that we are trying to reduce. To do this, the trajectory is updated to compensate for the error.

$$HT_t(i) = HT_{t-1}(i) - \beta \quad e \tag{10}$$

where β is the learning rate. The higher β is the faster the algorithm learns but precision is lost.

As the robot moves, new sensor information is received and the trajectory for the next cycle is updated. This process is carried out on the host computer and updates of trajectory points are sent to the robot at intervals of five points. When the robot reaches the end of the trajectory cycle, it resets the clock to zero and continues moving using newly updated trajectory points. This process continues until no further improvement is seen.

The effect of this learning is evaluated by calculating the average offset from the center during one cycle for all three dimensions. A natural evaluation function is a simple combination of the errors in all three dimensions. The work reported here weights all three components equally in a linear combination, but we are currently experimenting with other evaluation functions, including a quadratic combination to penalize higher errors.

Our results show that close to optimal trajectories are achieved in about a dozen iteration of the learning process, and that this takes less than 15 seconds. As a result, the robot can complete the learning in one short walk without the need to change directions during the learning process (unlike, for example, [15] though that was completing a more complex task). Since the robot uses only the attached sensor, no additional equipment is necessary beyond the host computer and therefore learning may be carried out in any conditions.

VI. Experimental Results

We used a hand tuned trot gait resembling a popular gait used by many teams in the Robocup competition. The gait is designed in a way such that the path of the feet resembles a half elliptical locus as shown in Fig. 5. The legs spend half of the cycle in the air and half of the cycle on the ground. The trajectory contains 100 points and the cycle of the gait is 800ms. This gait produces significant motion of the head in all three dimensions.

We let the robot walk and run the learning algorithm using a learning rate of .3. The experiment was stopped after 15 iterations when no further improvements could be seen. This experiment was repeated 10 times to show that the results are repeatable and improvement can be clearly seen every time.

The head movements as detected by the artificial vestibular system during the first and last iterations can be seen in Fig. 6. This graph shows the average offset obtained over 10 gait cycles. These values are the absolute movements of the head in space, as measured by the artificial vestibular system.

Fig. 7 shows the score of each dimension for each iteration, that is the error that is measured by the artificial vestibular system over time while learning is taking place. The dotted lines show individual runs of the experiment while the solid lines show the average results. This demonstrates that errors in all dimensions fall rapidly over just a few iterations of the learning process, and that the final average error is approximately the same in all dimensions. This final average error is less than 1 degree. The improvement is strongest in the pitch direction when a large deviation from the center can be seen in the movement before learning. The overall head motion was reduced by nearly 70 percent.

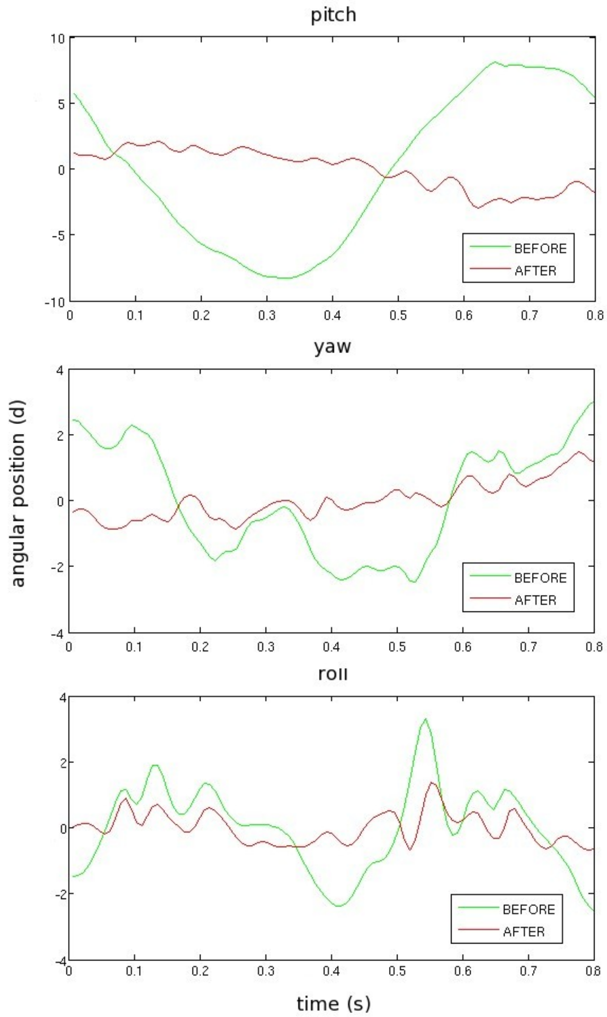

Fig. 6. Movement of the head during a gait as detected by the artificial vestibular system before and after learning. This is the average movement over 10 gait cycles.

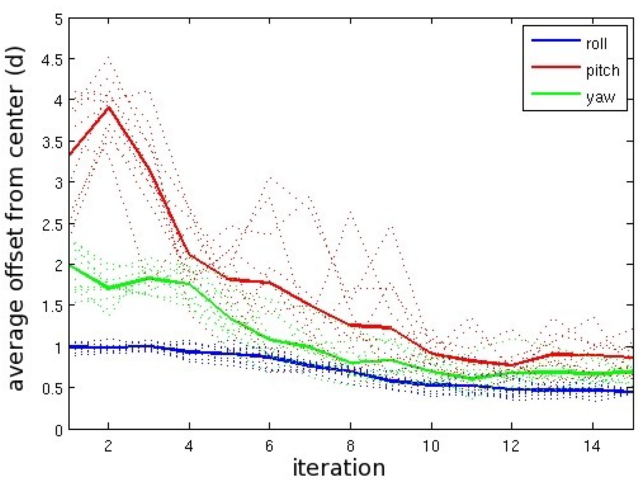

Fig. 7. Evaluation of learning over time

Sample learned trajectories after 15 iterations may be seen in Fig. 8. These are the relative motions of the head with respect to the body, that is the motion that the robot has learned to apply to its head to offset the motion induced by the gait in order to keep the head stable. Note that these trajectories are not simply the inverse of the starting error.

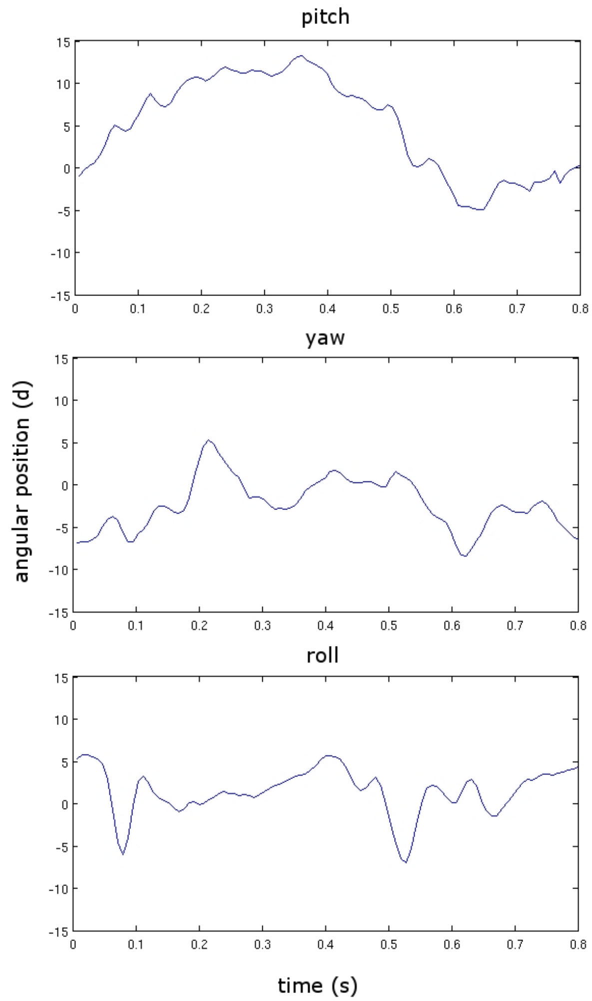

Fig. 8. Head trajectories for the pitch, yaw, and roll motors after learning.

VII. Conclusion

In this work we have shown that it is possible to us an artificial vestibular system based on primate biology to nearly eliminate the motion of the head during walking. While the system proved to be too slow to work in real time, with delays much higher than those seen in biological systems, compensatory movements can be learned in only a few seconds. If left active, the learning system should adjust the head trajectory when changes in terrain appear, which significantly affects the gait of a robot.

With the help of the learning approach, head movement was reduced to less than 1 degree on average in all 3 dimensions. This should be enough to prevent blurring of camera images and improve any tasks associated with vision. Further improvements may be achieved by mounting a movable camera and implementing the additional vestibulo-occular reflex as shown in [12]. These are lighter than the head of the Aibo, and driven by more powerful motors, so we can obtain a faster response than the Aibo is capable of.

For this paper we used a hand tuned gait as a starting point. In the future we plan to 1) start from the actual trajectories of leg motion in quadrupedal primate gait [16] and 2) incorporate the learning method presented here into a gait learning mechanism. In gait learning, each gait is evaluated for periods of time longer than our system needs to stabilize the head. This means that the additional gaze stabilization could be incorporated into existing gait learning algorithms with no additional runtime required. Using this methodology the learning procedure can search through a larger space of possible head and leg movements than in the work reported here (where the leg movements are fixed), and, as a result, we should be able to learn combinations of movements that further reduce head motion beyond what is achieved here.

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