# Biologically Inspired Turn Control for Autonomous Mobile Robots

Xavier PEREZ-SALA a, Cecilio ANGULO a and Sergio ESCALERA b

<sup>a</sup> CETpD-UPC. Technical Research Centre for Dependency Care and Autonomous Living, Universitat Politècnica de Catalunya,

Neàpolis, Rambla de l'Exposició, 59-69, 08800 Vilanova i la Geltrú, Spain <sup>b</sup> MAiA-UB. Dept. Matemàtica Aplicada i Anàlisi, Universitat de Barcelona, Gran Via de les Corts Catalanes 585, 08007 Barcelona, Spain

**Abstract.** An exportable and robust system for turn control using only camera images is proposed for path execution in robot navigation. Robot motion information is extracted in the form of optical flow from SURF robust descriptors of consecutive frames in the image sequence. This information is used to compute the instantaneous rotation angle. Finally, control loop is closed correcting robot displacements when it is requested for a turn command. The proposed system has been successfully tested on the four-legged Sony Aibo robot.

**Keywords.** Robot navigation, Path execution, Human motion, Turn control, SURF descriptor

#### Introduction

Navigation for autonomous mobile robots, independently of the platform and its task, implies to solve two related problems: path planning and path execution. Path planning can be defined as a high level robot guidance from a place to another place or from one orientation to another one, while path execution refers to low level processes needed to fulfill path planning decisions [6]. This work is about, given a certain path plan, how to ensure a successful turn control in path execution when the only available information for the robot is data extracted from its on-board camera. Remarkably, no landmarks in the environment are needed.

Unexpected robot behaviours can be observed during path execution when a system is asked for reaching a place or set point, though it acted properly in simulated or ideal conditions. Failures in path execution, even for simple path executions like a 'go straight forward' or 'turn 23°' path commands, are due to several reasons: noise in the sensors, damages in the actuators, perturbations, model errors or collisions. Consequently, a feedback control would be interesting to be implemented to correct the robot from possible motion deviations.

A common approach for obtaining feedback is to consider artificial landmarks [5,6]. However, for a general solution, no landmark should be considered. Another solutions focus on constraining robot motion and camera localization on the robot in order to ob-

tain robot egomotion [2,3,4]. Since nor robot configuration, neither camera localization will be constrained, but be placed in the front direction, egomotion can not be considered.

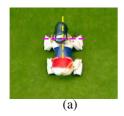
The general problem at hands is to ensure the execution of turning a certain angle by a general mobile robot endowed with a rotating camera, when the only available information are frames from the camera and angle measurement of the rotation parallel to the ground, between the robot and the camera. Examples of robot configurations which could use this algorithm are: biological inspired robots with "head" (mobile part of the robot where camera is placed) and "body" (the rest of the robot) joined by a motorized neck with encoders, or common robots with an embedded camera with pan degree of freedom. Our proposed approach starts rotating the head to the desired angle using its sensor. Then, the body of the robot is aligned with the head, maintaining its orientation. In order to maintain the focus of the head in the same direction, the robot rotation is computed and compensated. Similarly to other approaches based on optical flow [2], consecutive frames are used to extract an approximation of the robot movement, by observing 2-D displacements of brightness patterns in the image. However, unlike standard solutions, the robot rotation will be computed online by extracting Speeded Up Robust Features (SURF) from image key-points and computing its displacement, i.e. motion information from SURF robust descriptors of consecutive frames of image sequences provided by the robot camera. Optical flow is a measure closely related with motion field [1], i.e. the projection of 3-D relative velocity vectors of the scene points onto the 2-D image plane. During a rotation, motion field shows almost parallel vectors with the same length, closely related to the rotation angle. It is proposed in this work to achieve control of turn for mobile robots by computing rotation angle from the vectors of the SURF flow. This knowledge will be the only information needed to close the control loop, and to achieve the desired rotation.

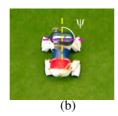
The rest of the paper is organized as follows: next section overviews the state-of-the-art methods for robot navigation based on optical flow. Section 2 describes the solution proposed for robot rotation. In Section 3, experiments are presented and discussed. Finally, conclusions and further research lines are listed in Section 4.

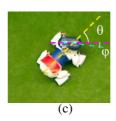
### 1. Background

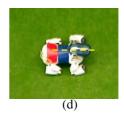
Visual based solutions for autonomous robot navigation are typically focused on path planning or path execution through localization computation. Whether it is possible to set-up the environment, standard approaches consist on the use of artificial landmarks to provide an accurate localization [5,6]. Otherwise, if some restrictions can be taken over the robot configuration (i.e. camera position or robot movement), solutions focus on egomotion computation [2,3,4] in order to fulfill a localization based on visual odometry. However, if nor environment is adaptable neither restrictions are taken, for a general solution it is proposed to keep away from previous approaches, mimicking human motion.

Human motion suffers a rapid evolution in childhood ages, during the period when children learn to walk like adults. Similarly to path execution in robots, goal-oriented locomotion in humans implies three abilities: localizing the visual target, controlling locomotor performance, and appropriately organizing visual-motor interface [10]. In early ages, spatial localization is achieved with respect to the child's own body position. In the









**Figure 1.**  $90^o$  rotation process: From any initial stage (a), robot camera is rotated in the desired angle  $\psi$  (b). Then, the body rotates in the direction where the head is pointing while the camera maintains the same orientation (c) until body and camera are aligned (d).

next stage, egocentric representation of the environment is abandoned while children use temporal landmarks present in the environment to organize the movements and positions, i.e. in order to fulfill intermediate goals in a path. Children finally walk like adult humans when become capable of building reliable exocentric topographic representations. Moreover, during the first years of independent walking, the head is progressively stabilized relative to space, facilitating the interpretation of the environment during locomotion. In addition, anticipatory strategies emerge to orient the head movements during locomotion tasks [10,11]. Anticipatory movements of eyes and head in the direction of the trajectory is essential in obstacles avoidance and, also, in following path constraints [12].

Simulating human motion, in a previous work it was presented a navigation control where, using the ideas of qualitative egocentric motion, it is performed a control to follow straight forward paths [14]. Visual features were extracted from robot camera through SURF flow, and used as temporal landmarks centered to respect the camera reference frame [13]. Inspired by human motion, a novel approach is presented here to control turns in robots with a rotating camera. Using camera as a "head", it anticipates turns in the direction the robot intends to go, facilitating the interpretation of the environment during locomotion. Moreover, SURF flow is also considered to compute the rotation angle and close the loop, controlling the robot turn.

### 2. Turn Control in Robot Navigation

A method to control turns during the navigation of mobile robots is introduced. A closed loop is implemented to control the robot turn, with feedback signal extracted from onboard camera images. The proposed procedure (Fig. 1) is composed by three steps: firstly, the head is rotated in the desired angle using its encoder, i.e. set point of the control is fixed. Next, in the *body alignment* step, through the use of SURF flow robot starts to rotate in the direction the head is pointing while camera is maintained in the same orientation. Finally, it is checked that turn is completed when body and head are completely aligned. At the same time, body-head alignment is composed by two simultaneous movements: body and head controls. Body control is responsible for rotating the robot, depending on the difference between body and head angles. Head control consists on maintaining the same head orientation during all the process, rotating the head in the same, unknown, angle but in the opposite direction.

## 2.1. Feedback Control

From any initial stage (Fig. 1(a)), the head is rotated to the desired angle  $\psi$  (Fig. 1(b)). In order to fulfill this step, a position control is done using the neck encoder <sup>1</sup>. Given this robot configuration, the process for body alignment rotates the body in the direction that the head was turned (see body turn in image sequence Fig. 1(b) - Fig. 1(d)), while head orientation is held during the same sequence. Hence, the alignment process is composed by two movements which have their own feedback control: body control and head control.

Body control searches for aligning the neck through rotating the whole robot, while head control regulates the head orientation using external references, balancing the robot turns by rotating the head in the opposite direction with the same, unknown, angle. Thus, the set point for body control is to recover head-body alignment, with error signal  $\theta$  being the angle between body and head, provided directly by the robot sensor: "pan" angle. Actuation is applied on the rotation velocity of the robot, since sensors are not used to define the robot orientation. On the other hand, head control, as described in Procedure 1, acts on the rotation angle of the head. A certain head orientation is performed in the first step of robot turning (Fig. 1(b)). Set point for this control is to maintain this orientation during all the process, by correcting, if necessary, turns suffered by the head when rotating the body. Hence, error signal in this feedback loop is the instantaneous rotation of the head  $\phi$ , which is inferred through SURF flow computation: it searches for the rotation which explains the distortion suffered by consecutive frames in an image sequence. Since the main control variable is the rotation angle, only the horizontal component of the error is considered.

# 2.2. Rotation angle

Nor artificial landmarks, neither fixed references are used for robot orientation. Hence, from the camera point of view, maintaining the same head orientation during all the process is similar to hold the same camera view (Fig. 2(b)), avoiding image distortions. It will be shown in this section how differences from consecutive frames (i.e. image distortion), computed through the use of SURF flow, allow to extract the rotation angle. Instantaneous rotation is computed from pixel displacements, knowing intrinsic camera parameters (assumed as motion field [1]).

For pure rotations, motion field displays all the vectors pointing almost in the same direction with the same length (Fig. 3(b)). Each one of them captures the distortion suffered by the image due to the camera rotation, because it is a relative change of orientation between the camera and the scene, that is supposed rigid. Moreover, pixel displacements correspond with motion field during instantaneous rotation, since it only depends on 3-D point projections in the image plane (pixel positions) and camera properties. Therefore, instantaneous rotation angle  $e^o_{x_k}$  can be computed as the mean of SURF flow vector modules  $\bar{M}_k$  and their angles  $\bar{A}_k$  (Procedure 1). Afterwards,  $e^o_{x_k}$  is cumulated until it can be sent to the controller, and it is used as error signal in the head control.

It could be argued that motion field during a pure rotation shows a very similar configuration to that obtained during a pure translation with only lateral displacement. In both cases, motion vectors are parallel. However, in the later case, their lengths are not the

 $<sup>^{1}</sup>Control$  for head rotation is provided by the robot framework <code>http://www.tekkotsu.org/</code>

#### **Procedure 1** Head control at instant k

**Input:** Current image  $I_k$  from the camera (Fig. 2(b)), keypoints from previous image  $P_{k-1}$ , angular precision pr, horizontal camera resolution  $res_x$ , and horizontal opening angle  $oa_x$ 

**Output:** Rotation angle:  $e_{x_b}^o$ 

- 1: **loop**
- Compute SURF descriptors and keypoint locations of  $I_k$ :  $P_k$ 2:
- Find temporal correspondences between  $P_k$  and  $P_{k-1}$ :  $M'_k$ 3:
- Calculate coarse angles of motion vectors  $M'_k$  with precision pr:  $C_k$ 4:
- Use statistical Mode as the most common angle  $Md(C_k)$  to refine correspondences:  $M_k$ 5:
- Calculate angles of motion vectors  $M_k$ :  $A_k$ 6:
- Compute means of motion vectors  $M_k$  and their angles  $A_k$ :  $\bar{M}_k$ ,  $\bar{A}_k$
- 8:
- Define horizontal error in pixels:  $e^p_{x_k} = |\bar{M}_k| cos(\bar{\bar{A}}_k)$ Transform error  $e^p_{x_k}$  to angles:  $e^o_{x_k} = e^p_{x_k} \left(\frac{oa_x}{res_x}\right)$ 9:
- 10: end loop

same, but inversely proportional to the depths of the corresponding 3-D points [1]. Since no landmark is considered, keypoint depths are not available and pixel displacements could not be considered a reliable approximation of motion field.

Motion field is not a directly accessible measure, but it is closely related with optical flow under certain circumstances [2]: (1) robot moves on a flat ground, with (2) on-board camera translating in parallel to the ground, and (3) its angular velocity is perpendicular to the ground plane. Unfortunately, for general robots like the one used in this work, constraints do not meet. The Sony Aibo robot is a quadruped robot with a camera on its "nose". Thus, image data is more instable than those provided by a wheeled vehicle with a camera mounted rigidly on its structure. Image instability is due to neck joints, causing head vibrations transmitted to the camera, and specially, for robot walking. Legged robot steps produce very different movements compared to wheeled robot displacements, usually smoother than quadruped robot's gait. Walk behavior in our experiments generates vertical and left-right pendular movements, i.e. camera suffers simultaneous roll and pitch rotations. Only the first assumption out of three is fulfilled in our case. However, since a pure rotation is considered, unfulfilled assumptions will not invalidate the optical flow approximation to motion field.

Due to robot configuration, rotation axis of the Sony Aibo robot does not match the axis of the camera rotation, as showed in Fig. 3 (c). This fact introduces an unwanted translation to the initial pure rotation, which will be considered as a perturbation, similar to camera vibration, and it will be assumed to be solved by the controllers. Algorithm introduced for head control ensures the camera orientation will be constant during the process, though the difference between rotation centers will incorporate a translation to the final robot position.

## 2.3. SURF Flow

SURF flow is defined as 2-D displacements of SURF patterns in the image, where SURF is referred to Speeded Up Robust Features [7]. It is the field resulting from correspondences between SURF keypoints from consecutive frames in a video sequence. Unlike optical flow or the more similar SIFT flow [8], SURF flow is not a dense flow. It is only performed between high confidence keypoints in the image, selected by using a multiscale Hessian detector to find image corners. SURF flow computation is faster than SIFT

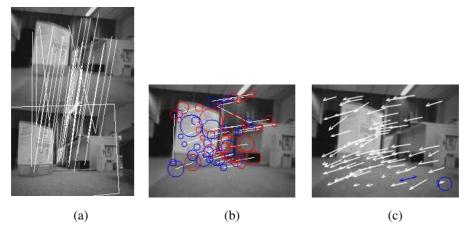


Figure 2. (a) Keypoint correspondences between consecutive images; (b) Motion vectors  $M'_k$  in the newest image; (c) Refined motion vectors  $M_k$  (white) with the correspondent mean vector  $\overline{M}_k$ ,  $\overline{A}_k$  (blue).

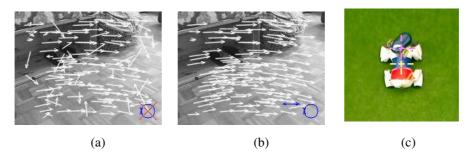


Figure 3. (a) Motion vectors  $M_k'$  (white) of SURF flow without refinement and warning (red) indicating the low confidence of the correspondences. (b) Refined motion vectors  $M_k$  (white) with the correspondent mean vector  $\bar{M}_k$  and angle  $\bar{A}_k$  (blue). (c) Rotation axis for head (pink) and body (yellow)

flow, since correspondences are only searched for a few hundreds of keypoints in each image (depending on the image texture), and corner detection and SURF description are computed using Haar wavelets on the integral image representation. Result of this correspondence is shown in Fig. 2(a) and Fig. 2(b).

Moreover, an image correspondence post-processing is applied in order to achieve a better mean vector  $\bar{M}_k$  (see Section 2.2). This refinement, showed in Fig. 3, takes place once SURF flow is extracted and the most common angle  $Md(C_k)$  is computed, given a certain angle precision pr (see Procedure 1). It consists on search for better correspondences for each keypoint in current image, looking for similar SURF descriptors in a restricted area of previous image. This search area is defined by the triangle ABC, where vertex A is the keypoint in current image, angle  $\widehat{BAC} = pr$  defines the search range and the middle point of the edge BC, the triangle size, depends of the velocity of the robot turning. Once correspondences are refined  $M_k$ , a more reliable mean vector  $\overline{M}_k$  is computed.

Method effectiveness depends, as usual, on assuming that keypoints are found in images, i.e. a textured environment exists. In fact, typical human-made scenes have enough

corners for achieving SURF flow performance. Moreover, SURF flow is robust to optical flow methods' limitations [9]: brightness constancy, temporal persistence or "small movements", and spatial coherence.

#### 3. Results and Discussion

In this section, we present quantitative results of our turn control framework. First, we describe the hardware and software, then, the environment where the test is performed and, finally, experiments are explained.

· Hardware and Software: We use the Sony Aibo ERS-7 robot wirelessly communicated with a standard dual-core PC. Experiments are performed using the robot for environment interaction and the computer for hard computation processing. Body alignment is divided in body and head controls. Body control is performed on-board as a reactive behavior, because it acts on rotation velocity of the robot depending on the angle sensor placed in the neck. By contrast, head control is executed in the external computer. Sony Aibo camera captures a  $208 \times 159$  pixel resolution image and it is sent to the PC every 100ms through wireless connection. The application running on the computer extracts SURF flow from consecutive frames, computing the mean vector and the rotation angle. Then, the angle to turn the head is sent to the robot. Gait behavior for the robot is based on the Tekkotsu software.

 $\cdot$  Environment: The experiments are performed in an artificial grass surface of about  $4m^2$  containing two crossing corridors. It is a natural scenario without artificial landmarks and small variability of the light level. In order to allow a future development in unstructured environments, corridor walls are wallpapered with pictures of real halls and corridors.

• Experiments: In order to achieve quantitative results of the system performance, two experiments are defined. In the first one, rotation angle of the head is measured through SURF flow computation and it is compared with pan angle, provided by neck encoder, with the purpose of know the reliability of the SURF flow approximation to motion field. The second experiment consists on measuring the performance of the rotation control proposed in this work, comparing our general approach with the one provided by Aibo Tekkotsu framework.

## 3.1. Rotation angle

In order to test the reliability of the rotation angle computation, i.e. the confidence of the SURF flow approximation to motion field, the robot head is turned in 5 representative angles. Then, rotation is measured through SURF flow computation and compared with the measure provided by neck encoder: pan angle. Angles are chosen below the middle of horizontal opening angle of the camera  $(oa_x/2)$  to ensure correspondences among frames, and 30 trials are launched for each one:  $3^o$ ,  $5^o$ ,  $6^o$ ,  $10^o$ ,  $15^o$ . Head turning is achieved using the provided module of the robot framework Tekkotsu. The results of this experiment are shown in Table 1. One can see that the values obtained for short angles are promising meanwhile they get worse for angles higher than  $6^o$ . For the three lowest angles both strategies present similar means. However, angle computation through SURF flow has more RMSE (Root Mean Square Error) than a sensor made for the specific task

**Table 1.** Angle measurements of head rotations by the use of neck encoder and computing the rotation angle through the use of SURF flow

		pan angle		SURF flow angle	
Set point	mean	rsme	mean	rsme	
3.0000	2.7328	0.3428	3.4359	1.0409	
5.0000	4.8138	0.3319	5.5745	2.5608	
6.0000	5.0072	1.7533	6.1324	3.1447	
10.0000	9.6855	0.4001	4.9603	6.5268	
15.0000	14.3472	0.6785	5.6386	9.9232	

**Table 2.** Angle measurements by a zenithal camera of robot rotations. Comparison between *open loop* rotation of a software made for Sony Aibo and *closed loop* rotation for any robot configuration

Set point	Robot framework		General approach	
	mean	rsme	mean	rsme
15.0000	11.6128	3.9981	4.7341	10.9956
30.0000	27.6286	4.7443	31.9155	6.7196
45.0000	42.8979	5.8573	41.1000	8.6912
60.0000	63.8203	5.8724	61.1852	9.7878

of sensing angles. This high variability occurs since we assume pure rotation, i.e. if camera axis match the image plane, however the head rotation of the Sony Aibo robot involves a translation. As shown in Fig. 3 (c), the rotation axis is on the neck and the camera is placed on the "nose" of the robot. In this sense, the obtained results for short angles confirm that SURF flow is a reliable approximation to motion field if the error introduced by camera translation does not produce significant changes on the measurements.

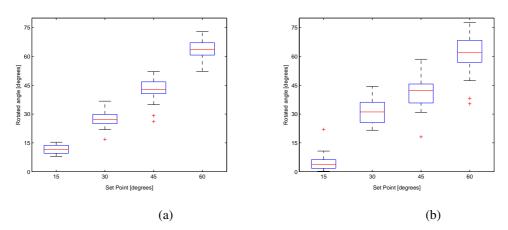
Based on the obtained results, in the turn control experiment we fix the maximum rotation velocity of the robot to  $3^o$  per frame (each 100 ms,  $30^o/\text{seg}$ ) in other to ensure a reliable sensing of the rotations.

#### 3.2. Robot turning

In order to quantify the performance of the biological inspired rotation control proposed in this work, the robot is turned in four representative angles, and the rotation fulfilled is measured using a zenithal camera. In addition, our general approach is compared with the turning control specifically configured for Sony Aibo, provided by the robot framework Tekkotsu. Angles are chosen below  $90^{\circ}$  and 30 trials are launched for each one:  $15^{\circ}$ ,  $30^{\circ}$ ,  $45^{\circ}$ , and  $60^{\circ}$ .  $90^{\circ}$  threshold is chosen since it is the maximum turn which the Sony Aibo head can fulfill. In order to measure the rotation angle, colored landmarks are placed in the robot head and tail, and the angle is automatically computed filtering by color the images taken from zenithal camera.

Tekkostu framework provides rotation modules for different robot platforms. However, the open loop control used for this experiment is specifically configured for the Sony Aibo robot. Thus, we used this control to test the performance of the proposed closed loop method, though it can be applied to any robot with a rotation camera. Results of this experiment are presented in Table 2 and Fig. 4.

Results show similar performance for specific Sony Aibo turn control and for our vision based approach, except for  $15^o$  rotation. During short angle rotations, angle be-



**Figure 4.** Angle measurements by a zenithal camera of (a) open loop rotation of a software made for Sony Aibo and (b) closed loop rotation for any robot configuration

tween body and head is small, and body control order a low velocity to turn the body. This causes that the robot feet slip and Sony Aibo will remain in the same orientation. For angles higher than  $15^{\circ}$ , the proposed rotation approach shows similar or higher mean performance than the specific control provided by robot framework. However, the the vision-based approach shows higher RSME than the robot framework. It is caused by SURF flow approximation to motion field, because of the error introduced by the neck encoder, and possible wireless connection problems.

In particular, some wireless connection problems were observed, losing some frames. When it occurs in consecutive images, the measured angle through SURF flow is not completely reliable and the final angle of the rotation is affected for this loss of information.

## 4. Conclusions and Future Work

We proposed a biological inspired turn control strategy for robot navigation. The novel approach is exportable to other robotic platforms and configurations, with the only requirement of having a rotating camera. Results shown that turn control is successfully performed without the use of artificial landmarks, taking into account that the robot rotation is a pure rotation, without translational component involved in the movement. The general turning control presented in this work is compared with a specific turn control

for Sony Aibo. In this scenario, our method showed an accuracy as good as the specific control for rotations over  $15^{o}$ .

Future work will focus on the exportability on different robot platforms and its extension to perform a full vision-based biological inspired framework for path finding, which can involve straight forward and rotation commands. Other improvements include decreasing sampling rate and the duration of actions.

# Acknowledgements

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