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Acoustic Flow-based Control of a Mobile Platform using a 3D Sonar Sensor

Jan Steckel, *FTI/COSYS-lab, University of Antwerp, Belgium and Flanders Make*

Jan.Steckel@uantwerpen.be,

Herbert Peremans, *FTEW/ENM Department,
University of Antwerp, Belgium*

Abstract—Moving a sensor through its environment creates signature time variations of the sensor’s readings often referred to as flow cues. We analyze the acoustic flow field generated by a sonar sensor, capable of imaging the full frontal hemisphere, mounted on a mobile platform. We show how the cues derived from this acoustic flow field can be used directly in a layered control strategy which supports a robotic platform to perform a set of motion primitives such as obstacle avoidance, corridor following and negotiating corners and T-junctions. The programmable nature of the spatial sampling pattern of the sonar allows efficient support of the varying information requirements of the different motion primitives. The proposed control strategy is first validated in a simulated environment and subsequently transferred to a real mobile robot. We present simulated and experimental results on the controller’s performance while executing the different motion primitives. The results further show that the proposed control strategy can easily integrate minimal steering commands given by a user (electric wheelchair application) or by a high-level navigation module (autonomous SLAM applications).

Index Terms—Ultrasonics, Beamforming, Broadband sonar, Sparse Arrays, 3D Sonar, Synthetic Aperture, Emitter arrays

I. INTRODUCTION

Sonar sensing has the potential to enable autonomous agents to perform intelligent interactions with their environment. While optical sensing seems to be preferred by most in the robotics community [1] nature has shown that it is indeed possible to have sonar based intelligent interactions with the environment. Amongst others, 1200 species of bats [2] and over 70 species of Odontoceti [3] rely predominantly on either in-air or in-water biosonar to navigate [4], classify complex objects [5] and to find prey [6]. Even humans can make use of sonar to navigate through their environment [7].

We would like to point to this existence proof from biology and argue, see [8], that using a sonar sensor capable of extracting sufficient information from the echo signal it should indeed be possible for engineered autonomous agents to use sonar sensing for intelligent interactions with the environment. Indeed, a number of robotic sonar systems have already been demonstrated that show how increasing the amount of information extracted from the received echo signal(s) can support significantly more intelligent interactions than simple obstacle avoidance. These demonstrations range from the intelligent use of multiple range sensors [9], [10] to array-based sonar systems [11] supporting robot mapping and localization applications. Taking more direct inspiration from

nature, biomimetic sonar systems have further been shown to be capable of simultaneously localizing multiple reflectors in 3D [12], recognizing different objects [13] or mapping free space in office environments [14].

As shown by the many examples of flying insects use of optical flow cues [15], [16], dynamic sensor cues contain useful and easily extractable information about both the spatial structure of an agent’s environment as well as its ego-motion through that environment. Furthermore, experiments with biomimetic robot models [17] indicate that these cues require minimal further processing to allow steering important basic navigation behaviors. While the use of acoustic flow cues for similar purposes in bats has only recently received attention [18], [19], software simulation studies [20] have shown the potential of such cues for guidance of bat flight.

In robotics, the use of acoustic flow cues has already been explored in a number of investigations. In [21] proof-of-concept robotic experiments are described that show that Doppler shift cues resulting from the use of long, constant frequency, calls contain sufficient information to implement rudimentary obstacle-avoidance and convoy navigation. The extraction of relative velocity to steer robotic obstacle avoidance behavior is described in [22]. In this paper, standard optical flow techniques are applied to artificial images constructed from binarized occupancy grids based on the readings of ultrasonic range sensors. In [23] acoustic flow cues are derived and preliminary experimental results are presented for the case of a monaural CTFM-sonar (Continuous Time, Frequency Modulated) sensor [24] observing a single reflecting object. The work described in [25] groups sensor readings belonging to the same environmental features using the ego-motion induced constraints consecutive sensor readings have to comply with. These approaches have in common that they make use of a sonar range sensor or a number of such sensors placed on a ring around the robot. We propose it is more advantageous to generate acoustic flow cues using a more complex sonar sensor capable of generating 3D position information for all objects in the frontal hemisphere of the robot [14].

In this paper we investigate how the acoustic flow field associated with this 3D sonar (analyzed in [26]) can provide, as is the case for the optic flow field, directly available, i.e. requiring limited further processing, cues sufficient to guide obstacle avoidance, corridor following and navigation of corners and T-sections. The same elementary robot behaviors

have been analyzed by various authors as they are well suited to act as building blocks for the realization of more complex robot navigation. In [27] these elementary robot behaviors are combined into a topological navigation scheme allowing a robot to move around in a corridor environment using a ring of sonar range sensors. To extract from the unreliable sonar readings reliable information that can be used to steer the robot considerable algorithmic postprocessing of the sonar readings is required. A more direct sense-act approach is taken in [28] where a stable control law to steer wall/corridor-following behavior while avoiding obstacles is derived using both sonar and odometry sensorial information. However, correct operation of the control law cannot be guaranteed using only sonar information as missing or occasionally erroneous sonar readings would interfere with the state estimate used by the controller. To realize more robust navigation behavior in realistic environments despite unreliable sensor readings Brooks proposed a layered control strategy [1], [29] combining the different basic motion primitives each driven by their specific sensory cues. Following this same approach [30] describes a behavior coordination framework combining the same set of building blocks to control a domestic robot also fitted with a ring of sonar range sensors for fetch-and-carry-type tasks. The behavior coordination, involving a combination of arbitration and fusion across behaviors, is based on the dynamical systems approach introduced by [31]. Again, due to the limited information provided by the ring of sonar range sensors additional algorithmic postprocessing is also required.

This last behavior coordination scheme is very similar to the one proposed in this paper, the most important difference being the use of the 3D sonar and the acoustic flow cues it gives rise to as input for the motion primitives. We propose that the 3D sonar sensor is particularly well suited for sampling the acoustic flow field set up by ego-motion of a mobile platform as it allows for the specification of particular regions of interest within the frontal hemisphere. Hence, this makes it possible to combine a broad field of view with selective sensory processing limited to the regions containing the salient cues required for steering a particular motion primitive. As this can be done after collecting the raw measurements, i.e. by postprocessing the sensor readings, it allows for a very flexible implementation of the 'matched filter'-principle described in [32] as a highly efficient way of fitting the sensor structure to the information needs of the agent. Indeed, as will be shown below, all control signals are defined as weighted sums of well-defined subsets of sensory output values making hardware acceleration of the processing straightforward to realize and thus allowing for minimal implementations on small embedded systems that could not support more complex path planning approaches. The main advantages of our approach are thus simplicity, robustness and low latency of the controller.

The remainder of this paper is structured as follows: in section II we introduce briefly the 3D sonar sensor. In section III we detail the acoustic flow model and how this can be used to perform motion control of a mobile robot. Section IV details the different motion primitives which are implemented on the mobile platform, and how the sensor data provides input to the corresponding control laws. Section V shows

both simulation and experimental results of a mobile platform performing the motion primitives described before. Finally, we draw conclusions in section VI.

II. SONAR SENSOR: ENERGYSCAPE GENERATION

We present a brief overview of the 3D sonar system used for the acoustic flow experiments. A more detailed description of this system can be found in [11]. The sonar sensor, see figure 1, is composed of a single emitter and an array of 32 microphones which are placed at known positions chosen at random in a rectangle.

A broadband FM-sweep is emitted (ranging from 20kHz to 50kHz), and the reflected echoes are recorded. Using matched filter techniques a pulse-compressed signal $s_i^{MF}[k]$ for every microphone i is created:

$$s_i^{MF}[k] = \mathcal{F}^{-1} \left\{ S_i^M(j\omega) \cdot S_b^*(j\omega) \right\} \quad (1)$$

with $\mathcal{F}^{-1}$ denoting the inverse Discrete Fourier Transform (DFT), $S_i^M(j\omega)$ the Discrete Fourier transform of the i -th microphone signal $s_i^M[k]$ and $S_b^*(j\omega)$ the complex conjugate of the Discrete Fourier transform of the emitted signal, as approximated by the signal sent to the DAC. In a subsequent array signal processing step an 'acoustic lens' is created which can be steered to arbitrary directions in the environment:

$$s_\psi^{BF}[k] = \sum_{i=1}^{32} w_i \cdot s_i^{MF} \left[k + \tau_i(\psi) \right] \quad (2)$$

The time-delays $\tau_i(\psi)$ are chosen to compensate the direction-dependent delays that the echoes experience due to the array geometry [33]. The weights w_i are chosen from a gaussian window over the array aperture. Finally, an envelope detection on the output of the beamformer for every direction is performed to arrive at the range-energy profile $s_{(\theta,\varphi)}^{EN}[k]$ for every direction. The combination of the range-energy profiles for all directions of interest is called the EnergyScape (ES), which is basically an acoustic 3D image of the environment:

$$E(k, \psi) = \begin{bmatrix} s_{(\theta_1, \varphi_1)}^{EN}[k] & s_{(\theta_2, \varphi_1)}^{EN}[k] & \dots & s_{(\theta_n, \varphi_1)}^{EN}[k] \\ s_{(\theta_1, \varphi_2)}^{EN}[k] & s_{(\theta_2, \varphi_2)}^{EN}[k] & \dots & s_{(\theta_n, \varphi_2)}^{EN}[k] \\ \dots & \dots & \dots & \dots \\ s_{(\theta_1, \varphi_m)}^{EN}[k] & s_{(\theta_2, \varphi_m)}^{EN}[k] & \dots & s_{(\theta_n, \varphi_m)}^{EN}[k] \end{bmatrix} \quad (3)$$

with discretized time/range denoted by k and direction denoted by ψ . In this EnergyScape, the direction ψ is expressed in a spherical coordinate system to denote the position of a reflector in the robot body reference frame by the vector (r, θ, φ) with $\theta \in [0, \pi/2]$ for the frontal hemisphere of the robot and $\varphi \in [0, 2\pi]$. The spherical coordinate system is illustrated in figure 2. The signal $s_{(\theta_n, \varphi_m)}^{EN}[k]$ is the range-energy profile formed by steering the acoustic lens to direction $\psi = [\theta_n, \varphi_m]$, followed by performing a matched filter and envelope detection operation.

III. ACOUSTIC FLOW MODEL

As our sonar sensor directly measures the (r, θ, φ) coordinates of reflecting objects, the acoustic flow model we propose

Fig. 1. The sonar system consisting of (a) a single emitter and an array of 32 microphones placed randomly in a rectangular envelope; (b) a delay-and-sum beamformer; (c) a matched filter and envelope extraction module.

Fig. 2. Position of reflector (r, θ, φ) expressed in the spherical coordinate system associated with the sonar system. The robot's reference frame is chosen to coincide with this coordinate system fixed to the sonar.

is a set of differential equations that relates the perceived change of location of these reflecting objects in 3D with the linear and rotational components of the motion of the sensor/robot. In this section, we briefly restate the acoustic flow model, a more detailed description/derivation can be found in [26]. The set of differential equations describing the change of location of reflector images can be written for each reflector at position (r, θ, φ) as

$$\begin{bmatrix} dr/dt \\ d\theta/dt \\ d\varphi/dt \end{bmatrix} = \begin{bmatrix} -\cos \theta(t) & 0 \\ \sin \theta(t)/r(t) & \sin \varphi(t) \\ 0 & \tan \theta(t) \cos \varphi(t) \end{bmatrix} \cdot \begin{bmatrix} V \\ \omega \end{bmatrix} \quad (4)$$

when pointing the sensor (x-axis) in the direction of the linear velocity vector and limiting the robot to planar (xy-plane) movement, i.e. rotations about its z-axis only (see [26]). In this equation V denotes the magnitude of the linear component of the robot ego-motion, and ω the magnitude of the rotational component. We assume these magnitudes to be constant for the duration of a single sonar measurement.

For a purely linear motion of the robot, $\omega = 0$, and the restriction of the imaging process to reflectors in the horizontal plane, $\varphi = \{-\pi/2, \pi/2\}$, this equation reduces to

$$\begin{aligned} dr/dt &= -V \cdot \cos(\theta(t)) \\ d\theta/dt &= V \cdot \frac{\sin(\theta(t))}{r(t)}. \end{aligned} \quad (5)$$

The solution to this set of differential equations has to comply with

$$\frac{dr/dt}{r(t)} = -\frac{d\theta/dt}{\tan(\theta(t))} \quad (6)$$

for $\theta_0 \neq 0$ with θ_0 defined as the angle between the robot path and the line of sight to a particular reflector at its first sighting, or equivalently

$$r(t) \cdot \sin(\theta(t)) = C \quad (7)$$

for $\theta_0 \neq 0$ with C a constant. This last equation describes an important invariant of the acoustic flow field: it predicts how a reflector's image first seen at angle θ_0 moves through the sensor's field-of-view when the robot performs a purely linear motion. The trajectories followed by various reflector images, called 'flow lines', can be seen in figure 3. Note that it is assumed that the centers of the emitter and receiver array coincide. Furthermore, as we also assume all reflections to originate from a point, i.e. generated by edge reflector, the offset between the two centers will also result in a small bias of the perceived position of planar and corner reflectors. This small discrepancy is caused by the receiver array determining the bearing of the virtual image of the transmitter in the case of a planar and corner reflector whereas in the case of an edge reflector it will determine the bearing of the actual edge reflector. Hence, in the case of a corner reflector the sonar images will not fall exactly on the contour lines derived for an edge-like reflector. Due to the small distance between the two centers compared to the much larger distances to the reflectors these discrepancies are ignored in the remainder

Fig. 3. (a) Motion invariant associated with reflector P for linear robot path (top view); (b) the $(r(t), \theta(t))$ trajectories (=flow lines) corresponding with the reflector images R , P and Q . We show reflector distances falling in the range of interest ($r \in [0, r_{max}]$) with r_{max} the maximum range of the sonar sensor. We further limit ourselves to the region in front of the robot ($\theta \in [-\pi/2, \pi/2]$), with negative θ values corresponding to the right half plane relative to the direction of motion of the robot.

of the paper. However, for an echo reflected from a planar extended reflector, the reflecting point on the planar reflector will move together with the sonar array. Consequently, the trajectory of the image of an otherwise completely featureless planar reflector is not one of the contour lines shown but a vertical line, i.e. the echo will be (approximately) reflected from the intersection point of the wall and the line through the receiver array orthogonal to the wall resulting in a constant image angle.

The motion invariant corresponding with a purely rotational movement ($V = 0$) derived from Eq. (4), i.e. $dr/dt = 0$, simply states that objects remain at the same distance when the robot rotates on the spot. As illustrated in figure 4 the trajectories of the reflector images will now be horizontal lines whose length is equal to the rotation angle.

IV. LAYERED ROBOT CONTROLLER

The linear and rotational motion invariants described above can be used to define a number of useful robot control laws [26]. Indeed, by segmenting the 2D EnergyScape, corresponding with the horizontal plane, in well-chosen subregions, as is illustrated in figure 4, the presence of reflector images in the different subregions can act as condition to trigger the appropriate motion primitive. The section labeled (i) is the so-called ‘collision avoidance’ region, and represents a circle around the robot that should remain free of reflecting objects at all times. The section labeled (ii) is the so-called ‘obstacle avoidance’ region, and represents a rectangular area in front of the robot. An object present in this area, will eventually lead to a collision if a purely linear motion is maintained. However, rotating the robot until the reflector image falls outside section (ii) is sufficient to avoid such a collision. The various motion

Fig. 4. By rotating the robot can avoid future collisions with reflectors whose images fall within the obstacle avoidance region (ii) before they enter the collision avoidance region (i) in $(r(t), \theta(t))$ -space.

primitives and their control laws will be explained in more detail below.

The overall architecture of the robot controller can be seen in figure 5. It is a layered control system inspired by the subsumption architecture proposed by Brooks [1], [34]. Note that, as one of the main applications of the system we are developing is a shared-autonomy electric wheelchair, user input is included as well. Typically, a user would input through the joystick both a linear and a rotational velocity command ($[V_u, \omega_u]^T$). These motion commands are subsequently modulated by the various control laws, each operating at a particular level of behavioral complexity. At the lowest complexity level resides collision avoidance, at the most complex level there is acoustic flow based corridor following.

The various sub-controllers, one for each motion primitive, are triggered when their associated conditions are fulfilled. The reactive corridor following is triggered when the user indicates (s)he wants to follow a corridor, the acoustic flow corridor following controller is enabled when the user indicates that (s)he wants to follow a corridor and the corridor condition (see later) is fulfilled. Obstacle avoidance is triggered when reflector images are present in region (ii) (see fig. 4) and collision avoidance is triggered when reflector images are present in region (i). Whenever the enabling conditions of more than one motion primitive are simultaneously true, the lower complexity controller will have priority over the higher level one. For example, a reflector image present in the collision avoidance region of the 2D EnergyScape will trigger the collision avoidance behavior which will modify the velocity commands coming from higher level behaviors.

A. Collision Avoidance

At the lowest level of control is what we call ‘Collision Avoidance’ (CA). This motion primitive is activated when an object enters the region of the EnergyScape labeled ‘(i)’ in figure 4. This object can be avoided by performing a pure

Fig. 5. Overview of the layered control system. The user inputs a desired motion command $[V_u, \omega_u]^T$, which is subsequently modulated by the layered control system. The system is layered in terms of decreasing complexity, i.e., more reflexive behaviors are more directly coupled to the robot motors.

rotation movement ($V = 0$), assuming the sensor update rate is sufficiently high compared to the robot forward velocity. The object is detected by windowing the complete EnergyScape with a binary mask R_{CA} which selects this region. If an ES-voxel in this region exceeds the noise threshold E_{CA} , the condition C_{CA} for enabling the CA-controller is fulfilled

$$C_{CA} : \exists r, \theta : E(r, \theta) \cdot R_{CA}(r, \theta) > E_{CA} \quad (8)$$

The robot rotates in the opposite direction of the closest reflector at a preset rotational velocity with linear velocity $V = 0$. The direction of rotation remains unchanged until the CA-region is cleared. As the robot can always trace back its approach path by making an about turn, this behavior is guaranteed to clear the CA-region. When this motion primitive is enabled it takes precedence over all higher level motion primitives and replaces all velocity commands with its own. It should be noted that this controller calculates the energyscape over the full 3D frontal hemisphere: 400 directions θ are chosen uniformly on a the frontal hemisphere using an equal area sphere partitioning algorithm.

B. Obstacle Avoidance

The second level of the control structure is ‘Obstacle Avoidance’. This motion primitive becomes active when one or more objects are present in the obstacle avoidance region of the EnergyScape, i.e. when condition C_{OA} (see Eq. 9) is fulfilled with the binary mask R_{OA} selecting the voxels belonging to region ‘(ii)’ from the EnergyScape (see fig. 4). An object in this region will eventually lead to a collision if the current linear motion is maintained ($\omega_{rot} = 0$). To avoid future collisions with objects present in this region, a control law inspired by a ‘potential fields’ method [35] is implemented.

While it is known that potential field methods suffer from local minima which in this specific case might delay obstacle avoidance in some circumstances, the user can always override the behavior at any time due to shared autonomy. This control law can be written as:

$$C_{OA} : \exists r, \theta : E(r, \theta) \cdot R_{OA}(r, \theta) > E_{OA}$$

$$\omega_{OA} = \omega_u + \alpha_{OA} \cdot \frac{\sum_{r, \theta} \frac{\cos(\theta) \cdot \text{sgn}(\theta)}{r} \cdot R_{OA}(r, \theta) \cdot E(r, \theta)}{\sum_{r, \theta} E(r, \theta) \cdot R_{OA}(r, \theta)}$$

$$V_{OA} = V_u \cdot (1 - \beta_{OA} \cdot \frac{\sum_{r, \theta} \frac{\cos(\theta)}{r} \cdot R_{OA}(r, \theta) \cdot E(r, \theta)}{\sum_{r, \theta} E(r, \theta) \cdot R_{OA}(r, \theta)}) \quad (9)$$

The first equation shows how the rotational speed given by the user is modulated to steer away from future collisions with objects in front of the robot. The repulsive force exerted by each reflecting object depends on its relative position with respect to the current trajectory. In particular, the object contribution depends on the angle, greater contributions for objects closer to the direction of travel, and the range, greater contributions for objects closer to the robot. The presence of an object is indicated by a non-zero value of the EnergyScape at the corresponding position whereby we represent the saliency of an object by its reflected energy, i.e. $E(r, \theta)$. Using the EnergyScape, i.e. reflector saliency, as a weight function a weighted sum of the repulsive contributions is calculated. The factor α_{OA} is an overall gain factor allowing to set the relative importance of the user and the sensor input to the controller, and is set to 1 in our experiments.

As is the case for the rotation speed, the linear speed is affected, i.e. decreased, more by objects which are close to the robot and lie close to the direction of travel. A similar saliency based weighing is performed and the trade-off between user and sensor input is again formalized by the overall gain β_{OA} , set to 1 in the simulation experiments.

When this motion primitive is enabled it takes precedence over all higher level motion primitives and replaces all velocity commands with its own modulated version of the user input. Note that we have chosen to control the robot speed adaptively instead of explicitly allowing for robot inertia or dynamics in the proposed controller. Indeed, as detailed above, when obstacle images enter the obstacle avoidance region, robot speed is reduced as a function of distance to obstacles until it falls to zero as an object enters the collision avoidance region.

C. Corridor Following

The most complex motion primitive in the current implementation of the system is ‘Corridor Following’. We have chosen to implement corridor following (CF) by combining two controllers: reactive CF and acoustic flow CF. The reactive CF controller is used to achieve approximate corridor following quickly. Once an approximate alignment with the corridor is achieved the acoustic-flow CF controller takes over to steer the robot to the centerline of the corridor and achieve stable corridor following. See figure 6 for a schematic representation

of how the images of the corridor wall features will show up in the EnergyScape.

1) *Reactive Corridor Following*: To achieve a first approximate alignment with the corridor, the reactive CF controller attempts to equalize the contributions to the EnergyScape in the left and the right peripheral regions by turning away from that region that contains most energy. This motion primitive becomes active when one or more objects are present in the peripheral regions of the EnergyScape, i.e. when condition C_{CFR} is fulfilled with the binary mask R_{CFR} equal to zero except for the peripheral angles ($|\theta| > 80^\circ$). This behavior was added to the control stack as it provides fast alignment with the corridor. In the absence of this behavior, obstacle avoidance behavior would avoid colliding with the walls but would not necessarily align the robot's path with the corridor. The control law can be expressed by:

$$C_{CFR} : \exists r, \theta : E(r, \theta) \cdot R_{CFR}(r, \theta) > E_{CFR}$$

$$\omega_{CFR} = \omega_u + \alpha_{CFR} \cdot \frac{\sum_{r, \theta} \left[\frac{-\sin(\theta)}{r} \cdot R_{CFR} \cdot E(r, \theta) \right]}{\sum_{r, \theta} E(r, \theta) \cdot R_{CFR}} \quad (10)$$

$$V_{CFR} = V_u$$

This control law again multiplies the EnergyScape $E(r, \theta)$ with a binary mask R_{CFR} and weights this product by the ratio of the sine of the reflector angles and the range resulting in a rotational speed ω_{CFR} . The gain α_{CFR} is set to 1. It should be noted that the sine function of angles close to $\pm 90^\circ$ produces values that are nearly equal to 1, and could be omitted. However, this implementation allows most freedom in the choice of the angular extend of the RCF-region, even for mask-sets that have larger opening angles. The linear component of the motion command is taken from the user input.

2) *Acoustic Flow Corridor Following*: Once initial alignment with the corridor has been achieved by the Reactive Corridor Following behavior, the Acoustic Flow Corridor Following (CF-acflow) algorithm is triggered. When the robot movement is aligned with the corridor centerline, all the images corresponding with reflections from features on the corridor walls will travel along two symmetrically placed flowlines in the EnergyScape, as can be seen in figure 6(a). If the robot moves along a direction that is not aligned with the corridor, the reflector images will travel along multiple flowlines, one for each reflecting feature, as illustrated in figure 6(c). To simplify the corridor following controller we propose that to measure alignment with the corridor we can integrate the EnergyScape activity along the different flowlines in the EnergyScape resulting in

$$\Gamma(d) = \frac{\sum_{F_d} E(r, \theta)}{|F_d|}. \quad (11)$$

In this equation, F_d stands for the flowline associated with the image of a reflector at a lateral distance d from the robot path, and $|F_d|$ denotes its length, i.e. the number of voxels lying on the flowline in the EnergyScape. The three different

Fig. 6. The flowlines traced out by the EnergyScape images of reflecting features of the corridor walls in case (a) the robot drives along the centerline of the corridor; (b) the robot drives along a parallel to the centerline of the corridor; (c) the robot drives along a direction not parallel to the centerline of the corridor. The width of the corridor is given by $2a$.

Fig. 7. The realizations of the function $\Gamma(d)$ in case (a) the robot drives along the centerline of the corridor; (b) the robot drives along a parallel to the centerline of the corridor; (c) the robot drives along a direction not parallel to the centerline of the corridor. The width of the corridor is given by the distance between the two peaks from (a) and (b).

scenario's the robot can be in when traveling in a corridor (figure 6) correspond with three different $\Gamma(d)$ realizations as illustrated in figure 7.

By acting on the $\Gamma(d)$ representation instead of on the EnergyScapes the control law can achieve more stable corridor following as it is no longer sensitive to the number and the precise location of the reflecting features along the corridor wall. In the current implementation, the CF-accflow controller is triggered whenever Γ consists of exactly two strong peaks and the signs of the peak locations are different, i.e. peaks fall on either side of $d = 0$.

Once the two peaks are detected, with the positions of the peak-maxima denoted by d_{PL} and d_{PR} for the left and the right peak respectively, the final control law can be formulated:

$$\begin{aligned} \omega_{CFA} &= \omega_u + \alpha_{CFA} \cdot (d_{PL} - d_{PR}) \\ V_{CFA} &= V_u \end{aligned} \quad (12)$$

with α_{CFA} a gain factor, set to 1 in our simulations. The linear speed is not affected by the acoustic-flow based controller.

V. EXPERIMENTAL RESULTS

To validate the proposed hierarchical controller based on EnergyScapes we have implemented a simulator using the Matlab environment. The robotic platform is simulated using 2nd order dynamic equations [36] for the Pioneer 3DX platform [37], and robot speeds ranging between 0.2m/s and 0.6m/s were used. The room impulse responses are simulated in 2D using a time domain approach allowing inclusion of the most relevant reflector types (edges, corners, planes [38]). The echo signals reflected by the environment are fed into a time-domain simulation (sample rate of 312.5kHz) of the sensor array using the known positions of the emitter and microphones. This generates 32 virtual microphone signals which are processed by the same beamforming algorithms used in the actual sonar array sensor (see [11], [39]). The

beamforming algorithms produce EnergyScapes in the horizontal plane (azimuth ranging from -90° to 90° in steps of 1°). The simulated sonar sensor samples the virtual environment at a sample rate of 5Hz corresponding with the measurement rate of the current prototype of the array sensor. A video showing various simulation runs as well as runs of the real robot is available as multi-media attachment to the paper. The same layered controller was then used to steer a real Pioneer 3DX platform fitted with the real sonar sensor through the corridor of our offices. The robot speeds ranged from 0.3m/s to 0.6m/s. An occupancy-grid map of the environment was produced using a Hokuyo laser scanner in conjunction with the ROS GMapping package during a separate, off-line mapping run. Furthermore, the robot has a gyroscopic correction of the odometry data. Subsequent on-line localization of the robot was performed using the Advanced Monte-Carlo Localization algorithm, also available as a ROS package. This algorithm uses robot-odometry combined with the Hokuyo laser-data to localize the robot. It should be noted that only the sonar sensor was used to guide the robot during the experiments. The laser scanner was merely used to localize the robot and record its trajectory.

As shown by both the simulation and experimental results presented below, the violation of the point-reflector assumption for planar reflectors has negligible effect on the results for multiple reasons. First, completely featureless planar reflectors do not often occur in real world environments. But even if they do occur, the obstacle avoidance motion primitive will be triggered as soon as the vertical line-trajectory intersects the boundary of the obstacle avoidance region (see Fig. 4), as will inevitably happen when the sonar moves closer to the reflector. Alternatively, when the movement of the sonar is approximately aligned with the direction of the walls of the corridor, the wall image will remain in a fixed position at the boundary of the (r, θ) -plane ($\theta = \pi/2$) and coincide with the images of all other reflecting features of this wall. Hence, it will be correctly taken into account by the Acoustic Flow Corridor Following motion primitive.

A. Corridor following

The simulation results shown in figure 8 illustrate the different types of trajectories taken by the robot when steered by increasingly more complex versions of the layered control system shown in figure 5. It can be observed that while the 'Obstacle Avoidance' behavior introduces anticipation into the robot's steering compared to 'Collision avoidance' behavior only, it is not sufficient to guarantee oscillation free movement through the corridor. The oscillations can be damped considerably but not eliminated completely by focussing attention on the echoes from the sides, i.e. from the walls of the corridor, as is done by the 'Reactive Corridor Following' behavior. Remaining oscillatory behavior is due to the simple echo energy equalization procedure assuming symmetric energy reflection which is regularly violated by the entering and/or leaving of particularly strong reflecting features in the current field of view on one corridor wall only. Adding the final 'Acoustic Flow Corridor Following' layer to the control system results in

Fig. 9. Experimental results for a simulated robot following a corridor of 2 meters wide with 10 randomly positioned reflectors on the corridor walls and varying initial robot positions and orientations. The histograms show the distribution of the distance to the corridor center for 100 runs during the whole trajectory. The experiment is performed under varying signal-to-noise ratios (SNRs), with SNRs of 40dB, 16dB, 8dB and 4dB. Please note the varying scales on the Y-axis.

a controller capable of both fast convergence to the centerline of the corridor and stable, oscillation free, tracking of the centerline independent of the distribution of reflecting features along the walls of the corridor. The same trend is also clearly visible in the results shown in figure 9, i.e. greater alignment with the centerline of the corridor as the controller includes more complex behaviors. From these histograms of the distance to the corridor centerline, it is clear that adding the 'Acoustic Flow Corridor Following' behavior to the layered control system yields very stable corridor following behavior, even under very low SNR conditions.

B. Corridor following in the presence of obstacles

To study the response of the robot when simple following of the corridor centerline is no longer possible we place an obstacle in the corridor (figure 10). All of the versions of the layered controller avoid bumping into the obstacle but, as before, the inclusion of 'Obstacle Avoidance' behavior allows to anticipate and avoid future collisions resulting in smoother travel. Adding the 'Acoustic Flow Corridor Following' behavior to the control system results again in the fastest recovery from avoiding the obstacle and reversion to stable tracking of the centerline of the corridor.

C. Corridor following on the real robot

After retuning of the respective gains of the different subcontrollers the same robot performance as observed in the simulations was shown by the real robot as can be seen from figure 11. The major retuning of the gain factors was necessary for the rotational gain factor in the acoustic flow corridor following. The gain was reduced from 1 to 0.1. This can be explained by the fact that the sensitivity of the sonar reduces significantly for the peripheral angles ($\pm 90^\circ$), which causes

Fig. 11. Experimental results for the real robot following a corridor of 1.8 meters wide, containing doors in the corridor walls as well as cupboards standing against the wall of the corridor. (a) shows two exemplary trajectories for different initial orientations of the robot (all subcontrollers active: CA+OA+CF+CFacc); (b) shows two exemplary trajectories for different initial orientations of the robot (Corridor Following subcontrollers inactive: CA+OA); (c) shows one of the exemplary trajectories of the robot indicating for each point on the trajectory what subcontroller was generating the motor commands (all subcontrollers active: CA+OA+CF+CFacc); (d) shows one of the exemplary trajectories of the robot indicating for each point on the trajectory what subcontroller was generating the motor commands (Corridor Following subcontrollers inactive: CA+OA).

the reflections of the walls to disappear quickly for rotational misalignment. Therefore, we had to make the controller less aggressive by reducing this gain factor. A similar reduction was found necessary in the reactive corridor following (0.25 instead of 1). The other gain factors were unaffected. We show the trajectories followed by the real robot with and without the Corridor Following capability.

Fig. 8. Experimental result for a simulated robot following a corridor of 2 meters wide with 10 randomly positioned reflectors on the corridor walls. Column a) shows exemplary trajectories for four controlling strategies with increasing complexity: Collision Avoidance (CA), CA + Obstacle Avoidance (CA+OA), CA + OA + Reactive Corridor Following (CA+OA+CF) and CA+OA+CF + Acoustic Flow Corridor Following (CA+OA+CF+CFacc). The last controller results in the most stable corridor following behavior. Column b) contains heatmaps illustrating the distribution of trajectories for 100 runs with varying initial robot positions and orientations and randomized reflector positions.

D. Negotiating a T-junction

Figure 12 shows what happens if the robot is confronted with a T-junction. If no user input is provided, a random direction is chosen depending on the initial conditions, the spatial distribution of reflecting features on the walls and the noise present on the measurements. If a user input is present, it introduces a bias into the rotation velocity (see Eqs. 9, 10, 12). These results show that this way of incorporating user input provides for intuitive and low bandwidth action selection without compromising the performance of the controller.

VI. CONCLUSIONS

In this paper we have demonstrated the closed-loop control of a mobile robot using a 3D sonar sensor and a layered control architecture consisting of multiple parallel, loosely coupled, reactive control laws. We have derived controllers for various motion primitives (collision avoidance, obstacle avoidance, corridor following) using an acoustic flow analysis of the images generated by the 3D sonar sensor. We have demonstrated the stability of the control laws in a wide variety of situations using extensive simulation-based experiments. Furthermore, we have demonstrated the robustness of the proposed approach by extending the simulated controller experiments to real-world robotic experiments using the same controller in combination with our sensor prototype and a Pioneer 3DX mobile robot.

The sensor-data presented to the controllers consists of B-scans of the environment, called Energyscapes. These Energyscapes can be created through post-processing the array measurements, requiring no extra measurement time, and the effective spatial sampling pattern can be adapted to each control-law independently. The simplicity of the controllers for the various motion primitives is due to this adaptation

of the sensor data to the control task. The programmable nature of the 3D sonar sensor's spatial sampling pattern allows experimentation with as well as effective implementation of the matched-filter hypothesis of biological sensor processing.

As is clearly shown by both the simulated as well as the actual robot experiments, the full controller tends to restrict the paths of the robot through the environment to a limited subset of all possible ones, i.e. a narrow band around the corridor's centerline. This path-restriction effect facilitates the implementation of a global navigation strategy that makes use of location recognition from the raw sensor data, such as the fingerprinting BatSLAM algorithm presented in our earlier work [14]. Hence, as the layered control algorithm was further shown to naturally incorporate steering commands from a higher-level navigation module, whether based on user input, e.g. joystick on a wheelchair, or a SLAM module our future work will extend the controller with such a navigation module.

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Fig. 10. Experimental results for a simulated robot following a corridor of 2 meters wide, containing randomly positioned reflectors on the corridor walls, with a cylindrical reflector of 10 cm diameter placed at position (10,1). Column a) shows exemplary trajectories for four different controllers with increasing complexity, column b) shows the distribution of the trajectories of 100 runs with varying initial robot positions and orientations and varying reflector positions on the corridor walls. The most complex controller still yields the most stable corridor following behavior, and re-converges most quickly after avoiding the obstacle.

Fig. 12. Experimental results for a simulated robot following a T-shaped corridor with randomized reflectors on the corridor walls. The different columns show the different types of controllers which are enabled (same as in the previous experimental results). The first row shows the results for the controller where user input provides a bias to the left side ($\omega_u = 0.2 \text{ rad/s}$), for 100 runs with varying initial robot poses and randomized reflector positions on the walls. The second row shows exemplary trajectories for the various controllers. The third row shows the behavior of the controller with a user input bias to the right side ($\omega_u = -0.2 \text{ rad/s}$), and the fourth row shows the behavior of the controller in the absence of user input ($\omega_u = 0 \text{ rad/s}$).

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