A spiking network for object detection in roving robots via a bionic antenna

Paolo Arena and Luca Patané

Abstract— **This paper proposes a neural-based model for ego-motion compensation in applications related to bionic antennae. Bionic antennae could be used on moving platforms to detect the presence of near range objects extracting a series of features like distance, material characteristics and the shape of objects. The introduction of a smart touching sensor on a robot could be very useful in different scenarios enriching the multimodal sensory system usually available on a navigation platform. The control architecture is based on spiking neurons and in particular a series of resonate and fire neurons has been used to extract important features from the sensory data. Simulation results and experiments performed on a roving platform are reported.**

I. Introduction

Bioinspired mechanisms and standard robotic applications are nowadays converging to find new solutions using two complementary approaches. Inside this scenario, bionic antennae can be considered an interesting case of study for integrating bio-inspired control solutions with robotic solutions.

As animals, robotic platforms that operate in different environment and interact with objects, need a large number and variety of sensory data that can be affected by disturbances also due to the voluntary movements of the system. In this case feedforward compensation methods can be adopted to compensate for disturbances that are accessible or can be extracted from other information.

Not only in humans but also in several insect species, an important function implemented by nervous systems is the prediction of the sensory consequences of actions. This mechanism can be formalized as a forward model that predicts the future state of a system given the current state and the control signals. The key point of forward modelling is that the system actual behavior should affect its upcoming sensory processing. Current research on forward models generally uses terms like "efference copy" referring to the output of the motor command system that is fed into the predictor, and "corollary discharge", to indicate the output of the predictor, i.e. the signal fed into the sensory system [1], [2].

In the proposed work a neural-based bio-inspired structure is proposed to process the information coming from the bionic antennae equipped on a roving platform as a first step for a further inclusion on a legged robot. From this prospective, the proposed approach is in some way related to how biological systems solve similar tasks. In fact there is a solid literature suggesting that biological systems use efference copy and internal model mechanisms to filter out disturbances in a fast, robust, and adaptive way [2]. An example is shown by male grasshoppers: interesting studies show that an auditory interneuron activity (G-neuron) is inhibited during stridulation (i.e. making a sound by moving hind legs and wings) [3]. Another interesting case is related to the work on crickets that are able to handle both phonotaxis and optomotor reflex integrating the two sensory modalities suppressing the ego-motion activity due to voluntary movements elicited by phonotaxis from the optomotor induced steering compensation. An interesting bio-inspired control architecture, including a forward model, is reported in [4], where a nonlinear feedforward compensator was designed as part of a bioinspired spiking neural network to model sensorimotor integration and control on a roving robot.

Another interesting work investigates the role of tangential neurons in the fly brain [5], [6]. These neurons are sensitive to the typical optic flow patterns generated during egomotion. starting from these neurobiological evidences an estimator consisting of a linear combination of optic flow vectors was proposed showing, in spite of its simplicity, excellent performances. Furthermore the use of forward models for prediction is ubiquitous and multiple examples can be found in nature. For instance, looking again at crickets, interneurons sensitive to antennae movement give less activation during active motion by the cricket itself [7]; the properties described in the reference suggest an involvement in the perception of objects in the path of the cricket.

The bionic antenna used on a roving platform consists of a rubber pipe, hosting a two-axis accelerometer, placed on the tip, used to acquire information about the oscillations induced on the antenna by the robot movements and when a bump occurs with an obstacle. The neural architecture here proposed to process the sensory signals, is based on a series of resonant neurons tuned to the band of frequencies characteristic of bumping events. By means of this structure, the ego-motion of the robot can be identified and also the position of a hit in the antenna can be extracted from the data.

Starting from these biological evidences, the basic theory of forward models will be presented in the next sections together with the potential applications to a bio-inspired touch sensor like a bionic actuated antenna.

II. Model description

The sensory data acquired from the antenna can be used to identify the presence of objects in the operative space of the robot. The intensive experimental campaign carried out to investigate the characteristics of the bionic antenna

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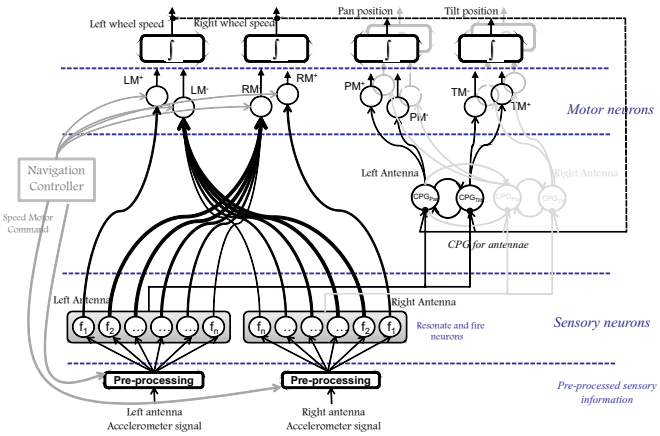


Fig. 1. Control architecture designed for the integration of the bionic antennae in the roving platform.

in different environmental conditions was fundamental to design a control architecture for the application of the bionic sensor in roving platforms. Different levels of processing have been considered as shown in Figure 1 where the sensory information after a preprocessing stage are elaborated by sensory neurons and through plastic synapses reach the motor neurons and then the muscle/motor system. The proposed scheme refers to the general case in which the robot is equipped with two antennae even if the current set-up includes only a single antenna. The use of resonant neurons to extract information from sensory data has been already applied by Webb and coworkers [8] where the capability of bushcrickets to respond to different song patterns was investigated and modelled. Moreover the implementation through spiking networks can be a first step toward a bio-inspired formalization of the structure that can be integrated within the relevant neural assemblies like the Mushroom Bodies and the Central Complex that can take a part in modeling these insect behaviours.

The sensory information coming from the two-axis accelerometer placed on the tip is pre-processed using the Principal Component Analysis and then normalized to obtain a suitable signal to be used as input current for a series of resonate and fire neurons. Each neuron is tuned to resonate at a specific frequency that belongs to the interval 7-25 Hz that contains the information we want to extract from the antenna. The neuron labeled as f_1 resonates at a frequency around 7Hz that, from the experimental campaign for the antenna characterization, is the natural oscillation frequency of the antenna in free motion and without any constrain introduced by hitting an object. The activation of neuron f_1 indicates that the antenna is moving and this signal is used to slightly increase the forward motion of the robot. The six neurons used to process the sensory signal for each antenna represent a sort of somatosensory map where the position of the contact between the antenna and an object is mapped. As already introduced the neuron f_1 gives information about the free movement of the antenna whereas the other neurons from f_2 to f_n are associated to collision detection in a point near the base (f_2) or near the tip (f_n) of the antenna. The array of resonate and fire neurons is connected to the motor neurons with plastic synapses. The synaptic efficiency can be assigned apriori to the structure to impose an avoidance strategy to the robot. Otherwise it can be learnt in a supervised way by using either a teacher or a reward-based paradigm introducing on the robot other sensors that can work as unconditioned stimuli using a classical conditioning learning paradigm.

Each antenna is actuated with a pan-tilt structure and a Central Pattern Generator (CPG) is used to actuate the movement of each joint. By changing the parameters of the diffusive connections between the CPG neurons (e.g. rotational matrixes can be used as reported in [9], [10]) it is possible to obtain different strategies for the exploration of the space in front of the robot. When two antennae are considered, it is also possible to create a diffusive connection between the two CPGs, to coordinate the antennae movements. When a collision is detected from the somatosensory map, the CPG activity is inhibited in order to stop the movement and allow the robot to disengage from the obstacle. Furthermore the current robot speed can be used to modulate the oscillation frequency of the antennae to reduce possible shadow areas that could cause sudden collision with obstacles.

The robot can be controlled only by the spiking system if a collision free navigation strategy is required but other higher level control layers can be added: in Figure 1 a block called Navigation Controller has been considered to this aim.

The control architecture can be further improved introducing a behaviour association network as proposed in [11]. The robot can try to perform different basic behaviour on the detected objects: for instance avoidance, climbing, pushing, and others, looking at the consequences of its actions. The robot by using a simple associative learning can choose the most suitable action for each object depending on information about dimension and type of material that can be acquired from the bionic antennae.

It is important to underline that the structure based on spiking neurons, can be considered as a sub-block that can be integrated with others parts for a more detailed control strategy. The link between blocks is performed using interneurons as already discussed in [12].

A. Neuron models and behaviours

In the proposed spiking network each unit is an Izhikevich spiking neuron [13]. The model is represented by the following differential equations:

$$\begin{aligned} \dot{v} &= 0.04v^2 + 5v + 140 - u + I \\ \dot{u} &= a(bv - u) \end{aligned} \tag{1}$$

with the spike-resetting

$$\texttt{if } v \geq 0.03, \texttt{ then} \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \tag{2}$$

where v is the membrane potential of the neuron, u is a recovery variable and I is the synaptic current and opportunely choosing the parameters a, b, c, and d different kinds of

Fig. 2. Dual drive robotic platform equipped with a pan-tilt actuated bionic antenna.

neural dynamics can be obtained. To show a resonate and fire behaviour the neuron parameters can be set to the following standard values: $a = 0.1$, $b = 0.26$, $c = -60$ and $d = -1$. Izhikevich neural models are well-known in literature and offer many advantages from the computational point of view.

III. Robotic Platform

The robotic system used for the implementation of the feedforward strategies, consists of a dual drive roving platform equipped with a pan-tilt actuated bionic-antenna, as shown in Figure 2.

The antenna is realized with a rubber pipe, the length is about 30 cm and on its top a two-axis accelerometer (i.e. ADXL321) is mounted. The antenna is actuated with two Dynamixel motors (i.e. High-performance networked actuators for robots RX-64 [14]) that can be controlled through an RS485 serial bus. The same motors are used also to actuate the four wheels motion. The electronic architecture used to control the robot is schematized in Figure 3. It is possible to distinguish two distinct control layers: a low level layer constituted by distributed micro-controller based boards interfaced with a high level controller, implemented on a notebook. Moreover a wireless communication with a PC is used for monitoring and debugging purposes.

Going deeper into details, the low level distributed control system is based on three main boards:

- An 8-bit Atmega-based board used to handle the ADXL321 sensor; the x and y signals coming from the sensor are sampled with a 10-bit ADC with a sampling rate of 1KHz, the data is transferred through an usb connection to a PC.
- A 128-bit Atmega-based board is used to control the pan-tilt system of the antenna; in the simplest case the two motors follow a limit cycle with a period of 2 seconds.
- The main board, based on a 128-bit Atmega microcontroller, is used to control the movements of the roving platform and can receive commands or exchange data with a remote PC through a wireless connection.

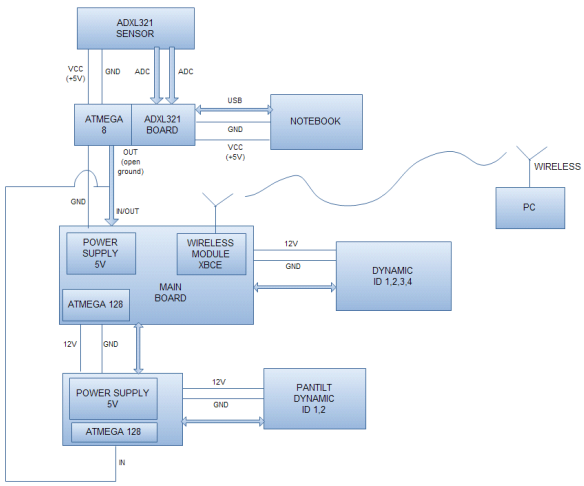


Fig. 3. Block diagram of the control system equipped on the robot.

The system is autonomous concerning power supply, in fact a Lithium-ion polymer battery is equipped on board.

A. Bionic antenna

The bionic antenna can be used as a smart sensory system like in the biological counterpart to improve the perception capabilities of a moving platform. The bionic antenna has been developed by the group of Prof. Duerr at the University of Bielefeld that, in the last years, successfully tried to exploit the possibility to use the antenna for spatial localization of objects and for material discrimination. The experiments were performed in a static environment with the antenna attached to a fixed support, by using signal processing techniques in order to extract information from the accelerometer sensor readings. More details can be found in several works produced in the last years [15], [16], [17].

Starting from these results we equipped the antenna on the pan-tilt structure embedded on a roving robot and performed a data acquisition campaign to characterize the smart sensor. The first trials were performed without moving the robot but moving the antenna to identify the effects on the sensor readings induced by the typical oscillatory motion of the pan-tilt that actuates the antenna. As can be noticed in Fig. 4 extracting the principal component from the two-axis signals and making a frequency analysis, an evident peak around 7.8 Hz can be distinguished. Therefore due to the antenna movements, a natural oscillation is induced on the sensory signals also in absence of collision with objects. This fingerprint can be considered as part of the effect of ego-motion, in this case the motion of the antenna, on the sensory system.

When the antenna collides with an object, an impulsive response can be identified in the sensor readings as shown in Fig. 5 (a). After the collision the antenna is maintained in contact with the obstacle for 1 second and a frequency analysis is performed as reported in Fig. 5 (b). In this case, a peak is detected around 11.8 Hz that corresponds to a

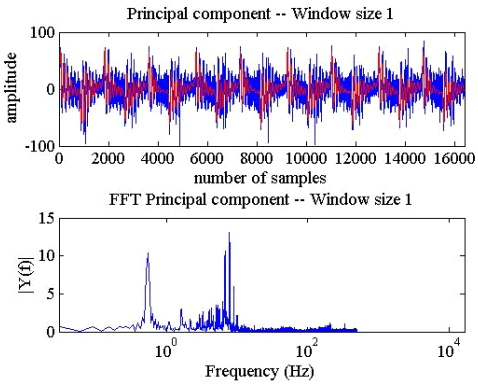


Fig. 4. Principal component of the two-axis accelerometer and corresponding FFT when the antenna moves following the oscillatory motor control signals sent to the pan-tilt, without moving the robot. The FFT of this signals underlines a peak around 7.8 Hz that represents the natural frequency of the antenna.

collision at 10.5 cm from the basis of the antenna. From the experiments it is easy to define a relation between the peak frequency and the position where the collision occurred on the antenna. If the contact point shift towards the tip of the antenna, also the frequency of the peak shift towards higher values as reported in Fig. 6 (a). From the performed experiments, the range in which the antenna is sensible to collisions goes from the base to few centimeters from the tip.

From the acquired data it is possible to perform a mapping between frequency peak and distance for our setup as proposed in [15]. A best fitting with a logarithmic function was obtained:

$$d = 37.89 log_{10}(F) - 29.82 \quad (3)$$

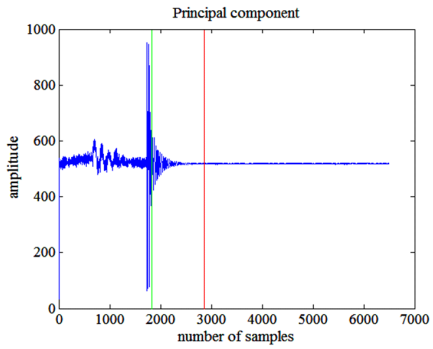
The comparison between experimental data and the fitting curve is shown in Fig. 6 (b). By using this map it is possible to localize the detected object in the space in front of the robot.

IV. Simulation Results

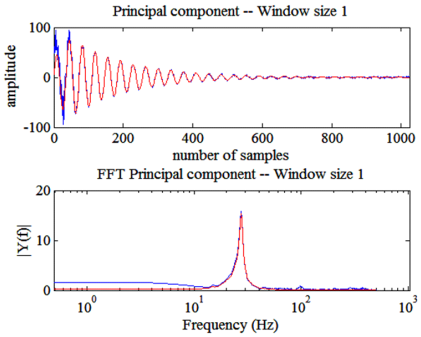
Starting analyzing the neuron behaviour, it can be noticed that modifying the neuron parameters we can obtain selective band-pass filters [13], [18]. For example choosing the parameters related to the neuron sensible to the 7 Hz components, and analyzing the frequency response, a very selective band pass filter behaviour can be obtained (see Fig. 7).

This strategy can be used to create a buffer of neurons acting as band pass filters as shown in Fig. 8. It has to be outlined that the resonant neurons, once designed to be frequency selective, completely substitute the FFT and do not need to wait a sample window before providing the output. It is only needed to reach the resonance condition and only the resonanting neurons emit spikes.

The neuron model is robust to noise, in fact the neuron behaviour in presence of disturbed signals is shown in Fig. 9 where the 7 Hz neuron is able to extract the information also with a high level of noise.

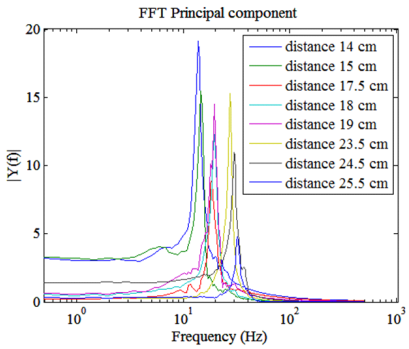


(a)

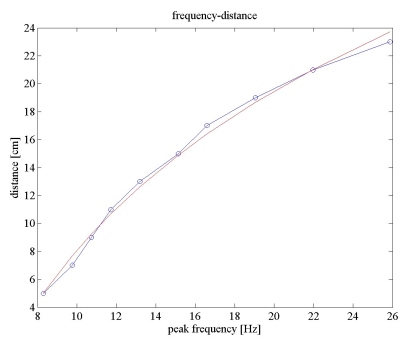


(b)

Fig. 5. Principal component of the two-axis accelerometer when the antenna collides with an obstacle (a) and corresponding FFT (b). The collision occurs at 10.5 cm from the basis of the antenna.



(a)



(b)

Fig. 6. FFT analysis obtained when the antenna hits the obstacle at different distance from the basis (a). More the collision is near the antenna tip, higher is the peak frequency. (b) Distance-frequency map experimentally obtained when the antenna collides with obstacles at different position and a logarithmic function used for the fitting.

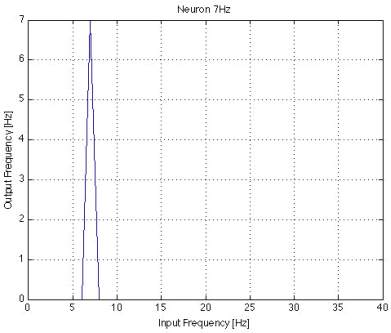


Fig. 7. Frequency response of the neuron with the parameters selective to the 7 Hz frequency component.

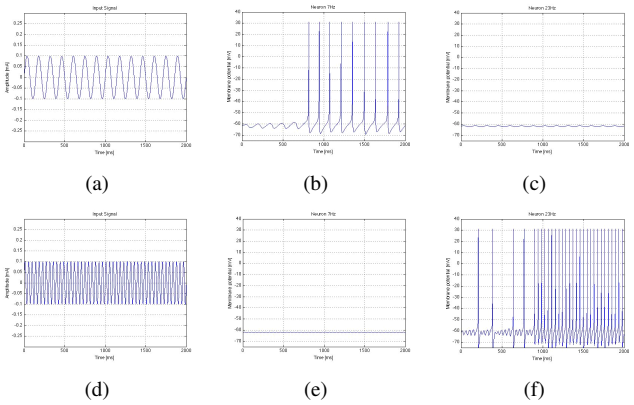


Fig. 8. Behaviour of two neurons tuned to filter signals with relevant components at 7 Hz and 23 Hz. As input signal a sinusoid at 7 Hz (a) and another at 23 Hz (d) have been used, the output membrane potential is reported: the response for the 7 Hz sinusoidal signal for the neurons tuned at 7Hz (b) and 23 Hz (c) whereas for the 23 Hz sinusoidal signal the response for the 7Hz tuned neuron is reported in (e) and for the 23 Hz tuned neuron in (f).

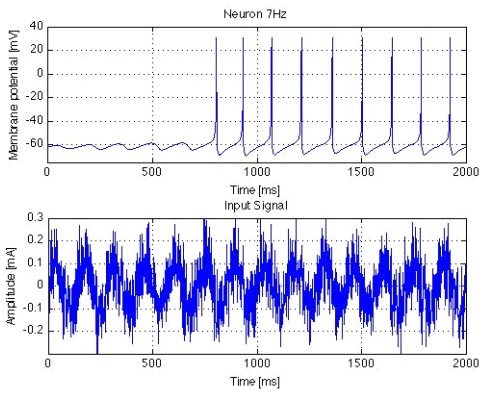


Fig. 9. Behaviour of the 7 Hz neuron in presence of a disturbed input, an uniformly distributed noise of about 40% of the input is added.

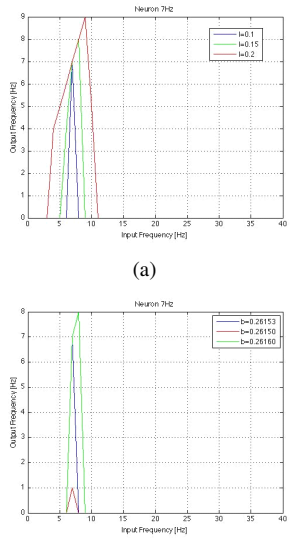


Fig. 10. Effect of the parameters used for the neuron tuning in the case of a 7 Hz specialized neuron. The integration time constant is used to select the frequency of interest, the input amplitude modifies the window in which the neuron is active (a) and the b parameter is responsible for the neuron response in terms of output frequency.

Changing specific parameters of the neuron it is possible to create the needed band pass filter. In particular the effect of the input signal amplitude is shown in Fig. 10.

The promising results obtained with simulated data where used as a starting point to apply the proposed neuron-based architecture to real data obtained in the experiments performed with the roving robot. The processing data flow used to obtain the reported results consists in a first phase of pre-processing of the raw data acquired by the accelerometer. The first step consists in a principal component analysis in order to work only with the principal component instead of the two channels of the accelerometer. It can be noticed that this stage is not strictly needed and the signals can be also processed separately by using the same steps reported in the following with the overhead of doubling the processing structure introducing an integration layer as a final stage to compare the information obtained from the two parallel paths. In a second step the signal is filtered through a low pass filter used to remove high frequency disturbance (over 30 Hz). The data is then centered around zero subtracting the mean value. The steps described above can be easily applied off-line elaborating the acquired stream of data but can also be performed online working with sliding windows. The obtained signal, as reported in Fig. 11, is then transformed in a train of impulses to be used as input for the resonant neurons. Among the different methods tested to obtain the input current, the strategy adopted consists in creating a bipolar signal considering the zero crossing as the triggering event.

Analyzing the first results obtained using this preprocessing strategy, it is evident that in some cases low amplitude oscillations can create artifacts that erroneously stimulate

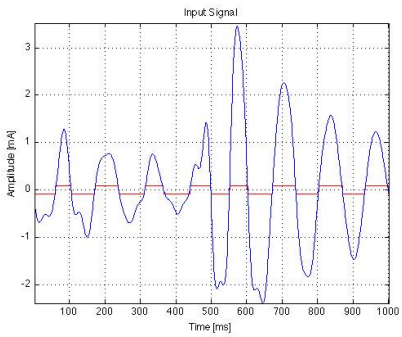


Fig. 11. Example of the signal obtained from the pre-processed accelerometer signals and the bipolar square wave used as input current for the resonant neurons. On the basis of the analysis performed a suitable choice for the input current amplitude is $I = \pm 0.085$.

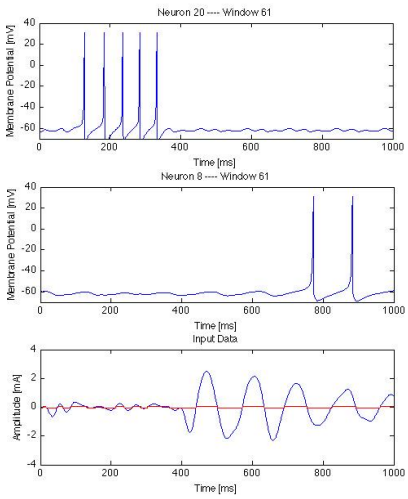


Fig. 12. Response of two different neurons of the array to a 1 second stream of data. From the bottom: the input signal and the output membrane potential of the resonators tuned to 8 and 20 Hz. The activation of the 20 Hz neuron is due to noise introduced also by the robot ego motion.

specific resonant neurons to fire. In Fig. 12 it is shown the pre-filtered data, the square wave and the response of two different resonant neurons. In this case the response of the neuron tuned for high frequency does not correspond to a real bump of the antenna and is only due to noise introduced by the robot on the sensor. To avoid this problem a threshold has been added and the subthreshold oscillations have been discarded. The value of the threshold could be critical because a not accurate choice for this parameter can lead to the presence of multiple fake bumps or on the contrary to miss collision detections. Moreover the noise that creates this problem in the data processing is in part introduced by the robot ego-motion and can consequentially be predicted by using the robot commands assigned.

A first attempt to adaptively select the threshold value consisted in finding a relation with the robot speed. If the robot navigates on a regular terrain depending on the speed the threshold can be modified improving the performance

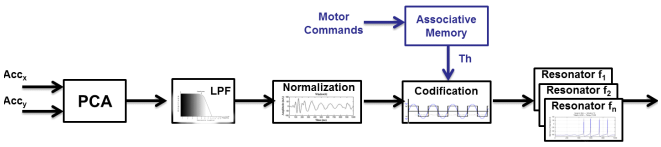


Fig. 13. Block diagram of the processing steps performed during the accelerometer signals elaboration. A PCA is used to elaborate only the first principal component, a low pass filter is then used to reduce the level of noise (ft=30 Hz), the obtained signal is centered in zero and is codified using a bipolar square wave, depending on the value of a threshold (Th), to be finally used as input current for the bank of resonators. The value of Th can be learned using an associative map like a Motor Map on the basis of the robot command signals (in particular the wheel speed).

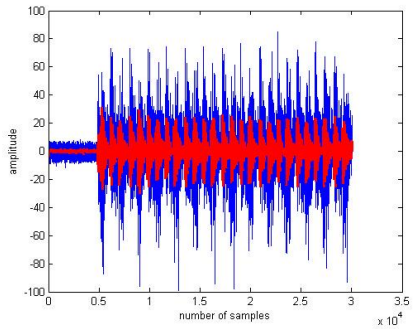


Fig. 14. Principal component of the accelerometer signal and the filtered data when a 30 Hz low-pass filter is used. the robot is moving at low speed and the antenna does not detect any collision.

of the control architecture. The idea is to make the robot able to learn the suitable values of the threshold using a reward-based method. A potential structure to be used is a Motor Map [19] where a lattice of neurons can be specialized to find the best threshold value for different robot speed. The structure can be easily extended to include more inputs taking care of other information like the type of environments. The reward signal can be generated by a teacher that indicates to the robot the collision events or using other sensors (e.g. sonar or infrared distance sensors) that can detect the event of interest (i.e. potential collisions with an obstacle). From a preliminary analysis a suitable value for the threshold during forward motion at different speed is $Th_{low} = 1.5, Th_{medium} = 2, Th_{high} = 5$.

A block diagram of the processing steps used in the proposed architecture is shown in Fig. 13.

To have a clear portrait of the different levels of processing, the data acquired during a simple experiment, where the robot performs a forward movement with low speed, is here reported. The principal component of the accelerometer data is shown in Fig. 14 together with the corresponding low-pass filtered signal.

The elaboration of the pre-processed signal is then performed working with time windows of 1 second. The behaviour of the system is shown in Fig. 15 where the analysis of a part of the whole data reported in Fig. 14 is given (i.e. interval [14200 15200]). It can be noticed from the FFT that a

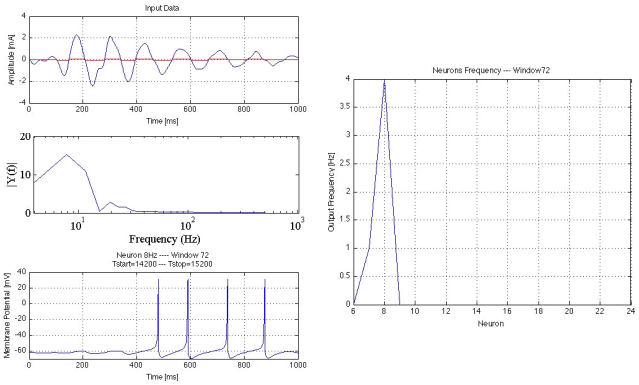


Fig. 15. Analysis of the signal in Fig. 14 in the time window [14200 15200]. Starting from the top panel: the pre-processed input data and the corresponding squared signal; the FFT that indicates the presence of a peak around 8 Hz; the Membrane potential of the neuron tuned to resonate at 8 Hz and, on the right, the spiking rate of the bank of filters in the given window.

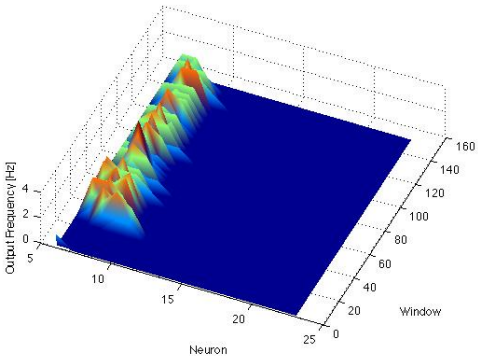


Fig. 16. Output spiking rate of the bank of resonant neurons during the experiment: the robot proceeds in forward motion without encountering any obstacle. The motion produce the activation of the neurons tuned around 7-8 Hz that represents the natural frequency of the system. Each window contains 1 second of data and is shifted for 0.2s to perform the successive elaboration.

peak around 8 Hz is present in the data and this information is evident looking at the spiking activity of the resonators where only the neuron tuned to respond to this range of frequency is active.

The behaviour of the bank of resonant neurons during the experiment is shown in Fig. 16 where the natural frequency of the antenna due only to the motion of the system also in absence of collision is easily identifiable in the map.

An experiment to evaluate the behaviour of the system when the antenna collides with obstacles is here reported. The Principal component of the accelerometer signal and the filtered data is shown in Fig. 17. The robot behaviour consists in a forward movement with high speed, when the bump is detected the robot and the antenna stop their motion for 1 second and then the robot goes backward to disengage the object and repeat the procedure.

In the whole experiment five different collisions can be identified. Analyzing the time window corresponding to the

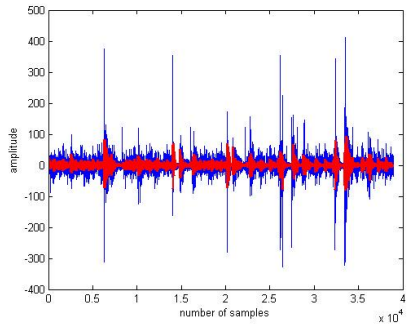


Fig. 17. Principal component of the accelerometer signal and the filtered data when a 30 Hz low-pass filter is used. The robot is moving at high speed and the antenna detects five different bumps.

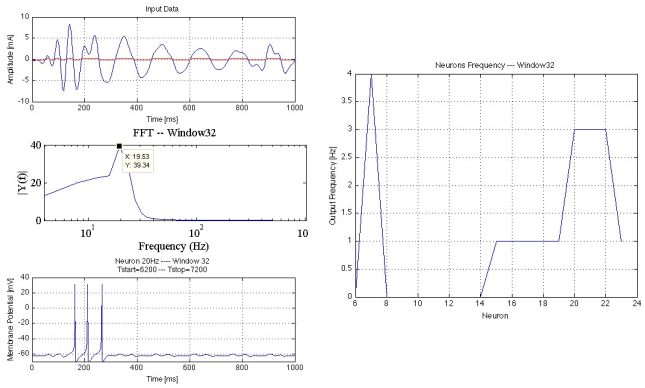


Fig. 18. Analysis of the signal in Fig. 17 in the time window [6200 7200]. The FFT that indicates the presence of a peak around 20 Hz; the Membrane potential of the neuron tuned to resonate at 20 Hz and, on the right, the spiking rate of the bank of filters in the given window is reported.

first bump [6200 7200] as shown in Fig. 18, the neural structure through the resonant neurons is able to detect the collision as also confirmed by using the FFT, recognizing a hit at a distance of about 18 cm (see Fig. 6 for the frequency-distance mapping). Taking into consideration another time window, [20200 21200] as in Fig. 19, another group of neurons resonates in the bank, from 12Hz to 14Hz, that correspond to a collision in an area around 12 cm from the basis of the antenna. Moreover extracting from the pan-tilt motors the position of the antenna it is possible to localize the obstacle in the area in front of the robot and if needed moving the antenna in different position the shape of the object can be reconstructed.

Finally the activity of the resonant neurons in time is shown in Fig. 20 where beyond the area around 7 Hz that is an indicator of the robot ego-motion, different peaks can be identified in correspondence to the collision events.

V. Conclusions

Bio-inspired solutions can be applied in robots to find alternative ways to deals with classical problems of obstacle detection in roving platforms. In this work a bionic antenna has been used to detect the presence of objects extracting

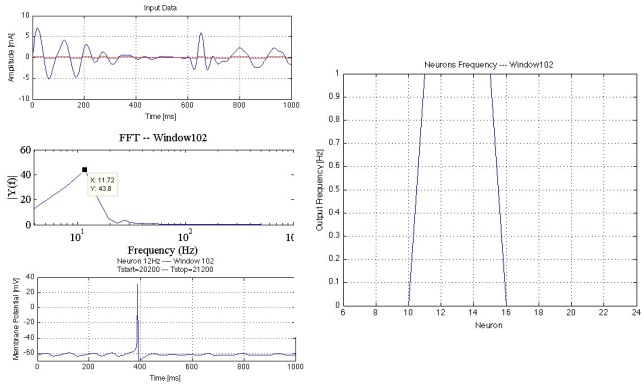


Fig. 19. Analysis of the signal in Fig. 17 in the time window [20200 21200]. The FFT that indicates the presence of a peak around 12 Hz; the Membrane potential of the neuron tuned to resonate at 12 Hz and, on the right, the spiking rate of the bank of filters in the given window is reported.

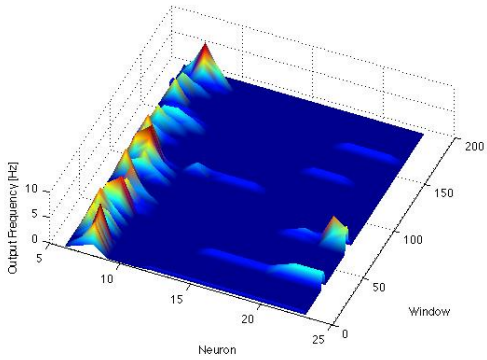


Fig. 20. Output spiking rate of the bank of resonant neurons during the experiment: the robot proceeds in forward motion, when a collision with an obstacle is detected the movement is stopped for 2 seconds then the robot proceeds backward to repeat the procedure. The Motion produce the activation of the neurons tuned around 7-8 Hz that represents the natural frequency of the system but the collisions are well identified in the map when higher frequency neurons resonate.

interesting features. A spiking network based on resonant neurons has been applied for processing sensory information in order to extract the needed results filtering out external noise and also internal disturbance produced by the robot ego-motion, following the paradigm of internal forward models. Simulations and experiments have been reported to evaluate the performance of the proposed neural-based control architecture. The bio-inspired solution proposed in this paper will be included into a more complex neural structure for learning and memory inspired by the insect brain. Therefore the paper represents a further important step toward the design of highly performing insectoid robots endowed with sophisticated and real time processing capabilities.

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