

Titulo Habituation based on Spectrogram Analysis

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Resumen In this paper we present a habituation mechanism which includes a modification of the Stanley's habituation model with the addition of a stage based on spectrogram to detect temporal patterns in a signal and to obtain a measure of habituation to these patterns. This means that this measure shows a saturation process as the pattern is perceived by the system and when it disappears the measure drops. The use of the spectrogram simplifies the detection of the temporal patterns which can be detected with naive techniques. We have carried on some experiments both a synthetic signal and real signals like readings of a sonar in a mobile robot.

Palabras claves Habituation, Multimodal interfaces, Robot Learning.

Tópicos: Robótica, Percepción y Visión Artificial

Aprendizaje Automático, Descubrimiento de Conocimiento y Minería de Datos.

Sección Paper Track

Habituation based on Spectrogram Analysis

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Abstract. In this paper we present a habituation mechanism which includes a modification of the Stanley’s habituation model with the addition of a stage based on spectrogram to detect temporal patterns in a signal and to obtain a measure of habituation to these patterns. This means that this measure shows a saturation process as the pattern is perceived by the system and when it disappears the measure drops. The use of the spectrogram simplifies the detection of the temporal patterns which can be detected with naive techniques. We have carried on some experiments both a synthetic signal and real signals like readings of a sonar in a mobile robot.

1 Introduction

Habituation and novelty detection can be thought as the two sides of the same problem because habituation begins when novelty finishes. Novelty detection is related with the discovery of stimuli not perceived before and habituation is related with the saturation process that living beings exhibit when the same stimulus is shown repeatedly, so habituation serves as a novelty filter [1]. Marsland [2] defines habituation as “a way of defocusing attention from features which are seen often”. Both process are involved in social interaction where robots and multimodal interfaces have to deal with a large amount of stimuli from the environment so it needs to filter it and to focus on *interesting* ones and leave out the rest. Therefore, there are two problem to solve: what is interesting? and when and how long a stimuli is interesting?. The former is task-dependent so it is considered to be outside the scope of this work. The answers to the latter questions are given by novelty detection and habituation.

With regard to the habituation, it has received great attention in the physiological and psychological areas. In the physiological area, some researchers have investigated the mechanisms of habituation of animals. One of the most known works in this area is the study of the Aplysia’s gill-withdrawal reflex [3] which led to the discovery physiological changes that are responsible for its habituation. Crook and Hayes [4] comment the study carried out on two monkeys (*macaca mulatta*) by Xiang and Brown who identified neurons that exhibit a habituation mechanism since their activity decreases as the stimulus was shown repeatedly.

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There are some models of habituation, although the proposed by Stanley [5] to simulate the habituation data obtained from the cat spinal cord is widely used. This model describes the decrease in the synaptic efficacy y by the first-order differential equation

$$\tau \frac{dy(t)}{dt} = \alpha(y_0 - y(t)) - S(t) \quad (1)$$

where y_0 is the normal, initial value of y , $S(t)$ represents the external stimulation, τ is the time constant that governs the rate of habituation and α regulates the rate of recovery. Equation (1) ensures that the synaptic efficacy decreases when the input signal $S(t)$ increases and returns to its maximum y_0 in the absence of an input signal.

The model given by (1) can only explain short-term habituation, so Wang [6] introduced a model to incorporate both short and long-term habituation using an inverse S-shaped curve,

$$\tau \frac{dy(t)}{dt} = \alpha z(t)(y_0 - y(t)) - \beta y(t)S(t) \quad (2)$$

$$\frac{dz(t)}{dt} = \gamma z(t)(z(t) - l)S(t) \quad (3)$$

where α , y_0 and τ have the same meaning than in (1) and β regulates the habituation and $z(t)$ decreases monotonically with each activation of the external stimulation $S(t)$ and model the long term habituation. Due to this effect of $z(t)$ after a large number of activations, the recovery rate is slower.

The organization of the rest of this paper is as follows. In section 2 some works about the use of the habituation and novelty concepts in different areas are commented. Section 3 introduces the spectrograms like elements to detect temporal patterns in signal. The implementation of the proposed method is explained in section 4 and finally some experiments are presented in section 5.

2 Related Works

The concept of habituation (or novelty detection) has been used in different areas like fault diagnosis, learning of temporal signals or learning in mobile robotics. In the latter one, some works are based on mechanisms of storage that act as short-term memories, therefore all the patterns not included in this memory are considered novel. Marsland [7] proposes an approach using as memory mechanism a SOM neural network. To add the short-term memory to the original network architecture, each neuron of the SOM is connected to an output neuron with a habituable synapses based on the model (1). To solve the drawback of the limited number of patterns that can be stored in a fixed size SOM, Marsland [8] proposes a modification of the HSOM to add nodes as they are required giving as result the GWR network. Ypma and Duin [9] also uses a SOM neural network as a novelty detector in the area of fault diagnosis. They give the the SOM a memory function as Marsland, but they compare the stored patterns with the

new using a new measure of map goodness. Crook and Hayes [4] also propose novelty detection based on a neural network, specifically a Hopfield network. The presence or absence of a pattern in the network is detected computing the energy of it, which has a fix computational cost, instead of recalling the pattern, which take several cycles.

Dasgupta and Forrest [10] propose a method for novelty detection using the negative selection algorithm that comes from the self-nonsel discrimination that exhibits the immune system. The immune system has developed a mechanism to detect any foreign cell (novelty). This mechanism has detectors which are strings that do match with no own cell, so a match implies a shift in the normal behaviour pattern and it normally corresponds to a foreign cell. In the work of Dasgupta and Forrest a set of detectors is generated according to the normal behaviour of the system and then if a pattern matches with a detector, it means that there exists a deviation in the normal behaviour, that is, it is novel. Habituation has also been used to train neural networks which realizes dynamic classification. The neural network of Stiles and Gosh [1] make uses of habituation units as input to a feedforward network to encode temporal information as well for classifications problems. The output of these habituation units is governed by the model (1) with its own value of α and τ for each unit. Chang [11] also makes use of model (1) to add a habituation mechanism to a neural network that learns obstacle avoidance behaviours. The habituation mechanism improves the performance of the learned behaviour when the robot is placed in a narrow hallway, reducing the oscillations that it exhibits without the habituation mechanism.

3 Spectrogram as Temporal Patterns Detector

In some systems, it is necessary to have a habituation mechanism to temporal pattern. For example a waving hand can catch the eye of a multimodal user interface but after a while without any other stimuli the system will exhibit a lack of interest in the waving hand, or if a face appears in its visual field, the system reacts focusing its attention in the face, but if it keeps static for a long time it can be a picture not a person. In this situations, it is necessary to provide the system of a mechanism that habituates to this repetitive or static location.

Here, an approach based on the spectrogram of the location of the stimulus is proposed. The spectrogram is a time-frequency distribution of the signal which is based on the Fourier Transform with a sliding window [12]. The following equation

$$\Phi(t, f) = \left| \int_{-\infty}^{\infty} x(\tau) \exp^{(t-\tau)^2/T^2} \exp^{-j2\pi f\tau} d\tau \right|^2 \quad (4)$$

gives the definition of a spectrogram with a Gaussian window function of half-width T , and it is the power spectrum of a signal which corresponds to the squared magnitude of the Fourier transform of the windowed signal. The window can have others forms apart from the Gaussian one. In Figure 1 we have the spectrogram of the signal that appears in Figure 2, where darker areas correspond

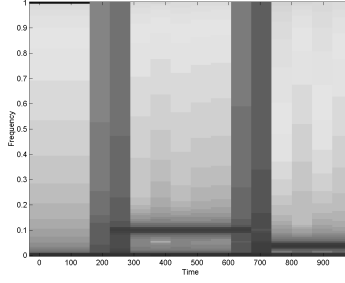


Fig. 1. Spectrogram of a signal

to higher power, so it can be observed that the frequency of the signal is changing twice over the time.

In the proposed approach, it is exploited the fact that temporal patterns of the stimulus have a specific pattern in the spectrogram. In the previous example, a fixed frequency signal corresponds to a straight line parallel to the time axis in the spectrogram, and the length of this line gives a clue about the time the stimulus is present.

4 Implementation

In this section the implementation of the proposed method is explained. The aim is to detect if the stimulus keeps a constant or repetitive location in the sensory space. To illustrate the method we utilise the test signal shown in Figure 2 which can be considered as the horizontal position of a stimulus in the visual field of a camera. This stimulus keeps a constant position at pixel 9 (12 sec.), then it oscillates around pixel 12 with a frequency of 2.5 Hz (18 sec.) and finally it moves to pixel 6 and oscillates with a frequency of 1 Hz (15 sec.)

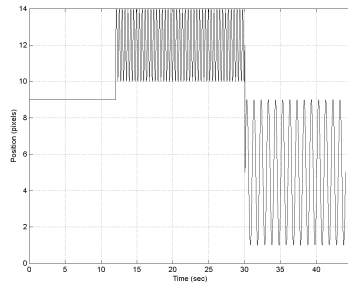


Fig. 2. Test signal

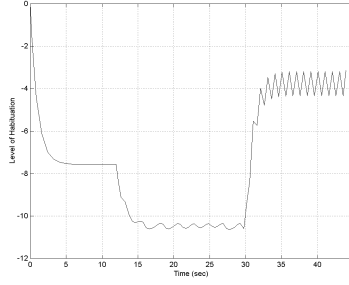


Fig. 3. Habituation model response to test signal

If we use the model of habituation (1) with the test signal, we get the response of Figure 3 which does not exhibit a habituation process in spite of the repetitive movement can produce habituation in some systems.

So it is necessary to add a previous stage to the model in order to capture the repetitive nature of the stimulus movement. This stage is based on a time-frequency distribution like the spectrogram, but in this case we do not have the complete signal to compute it, so the power spectral distribution (psd) is computed using the Fast Fourier Transform (FFT) in a window and then the power of the signal is obtained. The window to compute the spectrogram is slid as the positions of the stimulus are obtained, for example from a visual process. The psd gives the power of the signal at different frequencies so if we keep a trace of the frequency associated to the maximum power we can get the signature in the spectrogram and detect certain temporal patterns in the signal. Figure 4 shows the signature obtained with a rectangular window of width 256 as we have explained for the test signal. From analysis of the signature we can identified clearly three zones, each one corresponds to a different movement of the stimulus: one from 0 to 12 secs., the second from 13 to 31 secs. and the last from 33 to 44 secs. We have to note that there exists a delay between the change of the frequency in the spectrogram and the actual change in the signal. This delay obeys to the size of the window used to compute the FFT.

The identification of each of the previous zones in the spectrogram allows us to detect regularities in the position of the stimulus in the sensor space. Specifically, in Figure 4 each horizontal straight line corresponds to a periodical movement with constant frequency. To detect these horizontal lines we use a simple technique of fitting a straight line and then compute its slope; horizontal areas has zero slope. If we compute the slope of a fitted line using 10 points in the graph 4 and represent the absolute value of it, we get the graph 5, where it can be observed that the areas where the slope is null corresponds to the areas of interest in the spectrogram.

Once, the areas of interest are identified in the spectrogram with a value of zero, the habituation model (1) can be fed and it will exhibit the desired

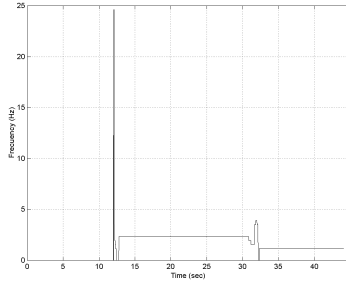


Fig. 4. Frequency of maximum power of the test signal using a window of size 256

behaviour of saturation after a while of being the stimulus in the same position or oscillating around a given one with a constant frequency (Fig. 6).

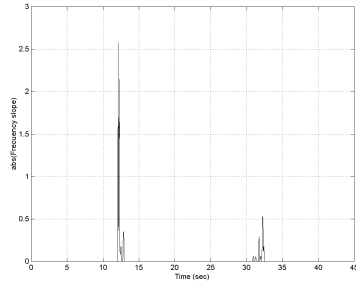


Fig. 5. Absolute value of the line fitted to the frequency graph

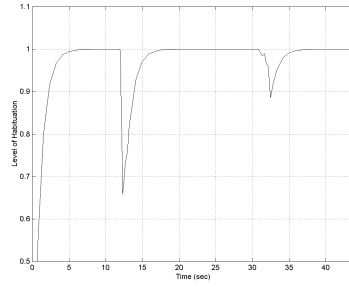


Fig. 6. Results of the habituation model after the detection of constant frequency movement ($\alpha = 1.0$, $\tau = 1.05$)

5 Experiments

In this section we show the results obtained with the habituation method we propose in this work. The first experiment corresponds to a problem of visual stimulus habituation. We present to a camera a yellow card (Fig. 7) and we move it after a while. Since the study of complex visual routines is out of scope of this work, we choose the yellow colour because it makes easy the detection of the card in the office environment where the experiments were carried out. For each frame of 384x288 pixels, we compute the position of the card and then we compute the algorithm described in section 4. The values of the

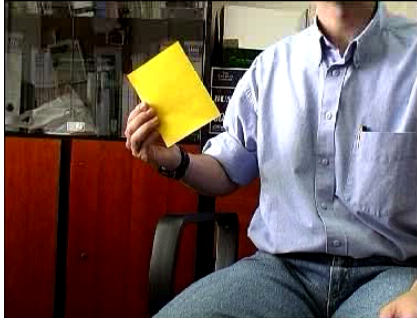


Fig. 7. Environment for the visual habituation experiment

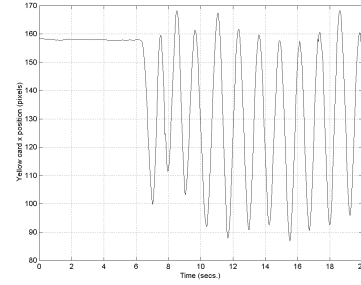


Fig. 8. Position in the x coordinate of the yellow card

x-coordinate is shown in figure 8 and the changes in frequency considered as changes in the slope of the fitted straight line are shown in figure 9. When the yellow card starts to move (6 secs.) there is a period where the frequency do not stabilises, but after 4 seconds the frequency is constant and it is detected correctly and the system habituates to this movement as is shown in figure 10.

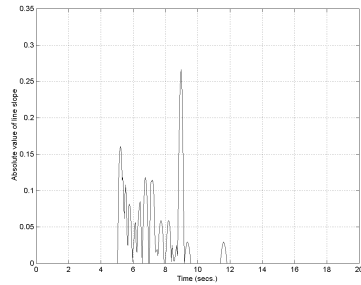


Fig. 9. Slope of the straight line fitted to the frequency change in the visual habituation experiment

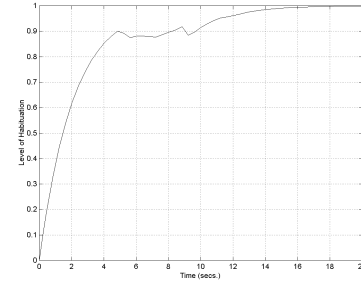


Fig. 10. Habituation level for the visual problem ($\alpha = 0.5, \tau = 1.0$)

This experiment was designed to study the habituation method proposed in this work in an environment of mobile robots and it consists of a mobile robot traversing in straight line the environment shown in Figure 11 and detecting the distance to the wall where there are holes/doors. The readings of the right sonar (Fig. 12) exhibits a repetitive pattern with noise due to the nature of the sensor (sonar). The frequency of the pattern is very low because the update rate of the sonars is 2Hz in this robot (Pioneer2) so the difference in frequency between the flat wall and the wall with doors is small (Fig. 13) and it affects to the change in slope of the fitted line (Fig. 14). The fact of having a small change in slope

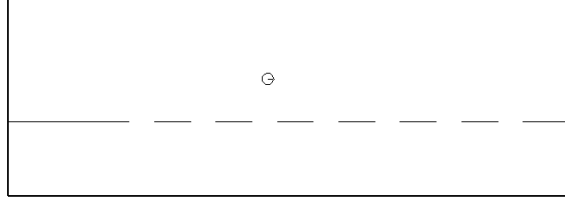


Fig. 11. Environment for the robot experiment

forces to decrease the parameter α to a value of 0.05 in the model (1) to slow down the recovery rate and thus introducing a break in the habituation curve (Fig. 15) when the robot leaves the flat wall.

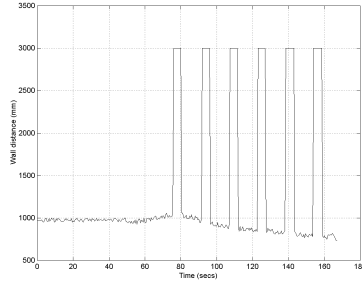


Fig. 12. Readings of the robot's right sonar along the corridor

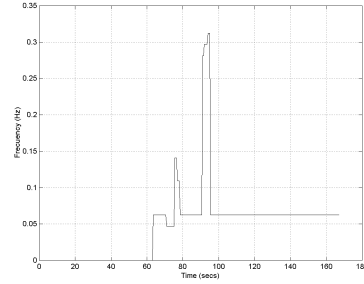


Fig. 13. Frequencies of maximum power for the corridor traverse problem

6 Conclusions and Future Work

In this work we have proposed a method to obtain a habituation measure to temporal patterns based on the use of a time-frequency distribution of the signal prior to a habituation model. The use of the spectrogram is due to the fact that temporal patterns in the signal domain correspond to signatures in the spectrogram which are easily detected by naive techniques like the study of the slope of a fitted straight line. Besides with the power spectrum distribution, the spectrogram can be computed incrementally so the habituation measure is obtained with a delay that depends of the window size used to compute the power spectrum distribution. We have tested the proposal in a problem of mobile robots using as signal the readings of the sonar which are noised and detecting correctly the two different zones in the corridor that the robot traverses.

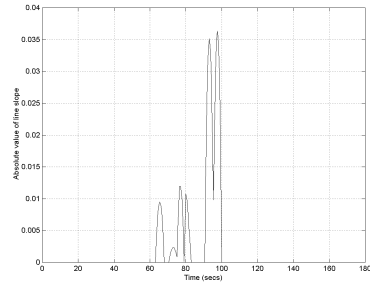


Fig. 14. Slope of the straight line fitted to the frequency change in the robot problem

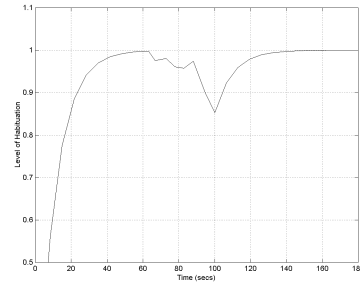


Fig. 15. Habituation level as the robot traverse the corridor ($\alpha = 0.1$, $\tau = 1.0$)

The use of the model proposed by Stanley as habituation mechanism, implies the need of adjusting the parameters α and τ to control the recovery rate which depends in this proposal of the difference in frequency of the temporal patterns of interest. Therefore, a future work is to obtain a relation between the difference in frequency and the optimum α value to avoid to tune it by hand. Also, it is necessary to extend the study to other temporal patterns apart from those with constant frequency and the effect of those patterns in the spectrogram.

Acknowledgements

This work has been partially supported by Canary Islands Regional Government under Research Project PI2000/042.

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