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The paradigm of Non-linear oscillators in image processing

Abstract- Image contrast enhancement is realised by using nonlinear oscillatory theory. Two different uncoupled networks based on nonlinear oscillators have been studied. Simulators for both networks are developed and tested with very low contrasted images. Results show a possible effective area of application of nonlinear oscillators for image processing tasks.

Keywords: oscillator, uncoupled network, Duffing oscillator, Van-der-pol oscillator, contrast enhancement, image histogram

1. Introduction

Since the beginning of the research in the field of machine-vision, problems of how to be able to get an unambiguous image and how to segment an image effectively have been of prime importance as these are the two major tasks amongst others needed to be done before further processing of an image. Things become more complicated if we are going to address these issues in a continuously changing environment such as dynamic driver assistance systems. In systems like these, addition of the requirement of real time response makes the overall scenario more challenging. A continuously changing environment requires the system to be adaptive, i.e. the system should process the input image in such a way that the corresponding output image always presents the best possible visibility regardless of the effect of different environmental conditions on the input image like darkness, raining, fog etc. This implies that the output image should contain a considerable amount of contrast in it so that all of the objects contained by the image are distinguishable easily by the system for further processing. This is a crucial need of dynamic driver assistance system. Image segmentation is another equally important task for the driver assistance system which enables the system to focus only on key information i.e. features of images related to the driving process. Such features may represent vehicles, road boundaries, traffic signs etc. It implies that we need a system capable of managing adaptivity and segmentation issues in real time.

The state-of-the-art shows the possibility of addressing these issues (i.e. contrast enhancement, image segmentation) using the concepts of nonlinear oscillatory theory. Non linear oscillators have been used successfully in many image processing areas like extraction of images from noise, amplification of images, halftoning, parallel extraction of regions of equal intensity or color, determination of common and distinct parts of images, moving elements, points of extrema, contours, etc [13]. Their characteristics such as self-organising, self-sustaining, automatic performance, and adaptivity being exhibited in a coupled or a uncoupled network, make them ideal candidates for solving the issues like contrast enhancement [1] and image segmentation [2-12]. It is worth mentioning here that the nonlinear oscillatory networks have been extensively investigated and implemented for image segmentation problem in particular. *The oscillatory networks provide resistance to image noise and adaptation to the local features of an image. Another feature of oscillator network is its possibility of VLSI implementation. In addition to these, a prediction can be made about their stability and synchronizing behaviour, making the overall system more robust.*

In this paper, we focus on using nonlinear oscillatory network to solve image contrast enhancement problem. We discuss two different uncoupled-networks based on nonlinear oscillators. The first network performs image contrast enhancement based on Duffing oscillator whereas the second network solve the same issue by using Van der pol-Duffing oscillator. Simulators for both networks are developed on Matlab platform and images having weak contrast with different initial conditions have been tested. The results reveal a very appealing possible area of using nonlinear oscillatory theory, i.e. image contrast enhancement.

This paper is organised as follows. Sec-2 gives an overview on image contrast enhancement problem and explains how we do measure the contrast of the image with our approach. Sec-2 is then divided into two sub sections explaining Duffing oscillatory network and Van der Pol-Duffing oscillatory network. Each subsection contains different results with input-output images, corresponding gray-level histograms and also show how the image contrast evolve under the influence of the oscillatory network. Sec-3 provides some concluding remarks with an overview on the presented results and suggests some directions for further research in this particular area.

2. Contrast Enhancement

Contrast enhancement is the phenomenon of increasing the difference in the gray-levels of the coherent regions.

An image having a good contrast, presents good visibility and it is easy to recognise all the objects present in that image. An image with a low contrast, does not present a clear scene and objects it contains are not clearly noticeable. In a low contrasted image, the pixel-values (grey-levels) of all the pixels are very close to each other. It means that the difference between any two pixels of the image is very small. In a high contrasted image, the gray-level values of all the pixels have a considerable difference among themselves. It means that the difference between any two pixels belonging to different regions is high.

An image may contain thousands of pixels. So to measure numerically that how much contrast is in this image, we just need two pixels from that image. One pixel should possess the highest gray-level value and the other pixel should possess the lowest gray-level value in that image. Then we calculate their difference, i.e.

Contrast difference = (Max gray level) – (Min gray level)

This difference gives an idea about the contrast present in that particular image. If this difference is very small then it means that respective image has a low contrast and if this difference value is considerably high then it proves that the underlying image has a good contrast. Why we choose these two specific pixels? Because by choosing the maximum and minimum pixel values from the underlying image we are sure that all of the rest of the pixel values of the image lie within these two limits. If the difference between these two limits (maximum and minimum) is high, then obviously the pixels within these two limits, are supposed to have considerable difference in their values, i.e. the values of those pixels are not so close. In other words, we may say that if difference between maximum gray-level value and minimum gray-level value is high, then the pixels between these two limits are spanned over a large range; hence they show a remarkable difference in their values. The inverse is also true for low contrast.

We here consider two approaches based on nonlinear oscillators to perform this operation. We check the contrast dynamics by observing the contrast difference calculated as described above.

2.1. The Duffing Osillator

The Duffing oscillator is a classical model widely studied due to its nonlinear dynamics. We here consider its one special form, i.e. a Duffing oscillator with double well potential. Its dynamics are controlled by the following 2nd order nonlinear differential equation.

(1) $$\frac{d^2x}{dt^2}+ax+bx^3=0$$

Where a and b are real number constants, b is also known as Duffing coefficient and it controls the cubic nonlinearity. To observe a double well potential a must be negative whereas b must be positive. Following Fig-1 shows the graph for Duffing oscillator with two-well.

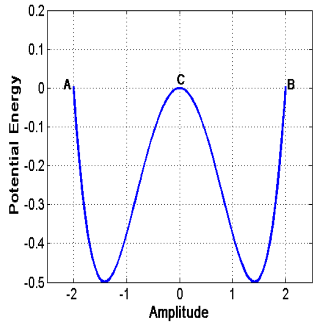


Fig. 1 The Duffing oscillator with two-well potential

potential. The potential-amplitude graph of the double well potential oscillator indicates that there are three points having equal potential energy. These are indicated as A, B and C in Fig.1. An object which is allowed to fall freely from point A or B, is able to cross C barrier and may enters into the other well. If the same object is now allowed to fall just below than point A or B, then it does not have enough potential energy to cross the central barrier C and would continue its rhythmic movements into the same well(in case there is no damping). This example gives the key idea of using Duffing oscillator for contrast enhancement operations. Two pixels having very close initial values may exhibit a big difference in their values over time once those are handed over to the dynamics of the Duffing oscillator with two-well potential.

For contrast enhancement operation, we consider an uncoupled network of Duffing oscillators with each oscillator of type eq(1). The network takes the form as given under,

(2) $$\frac{d^2x_{i,j}}{dt^2}+ax_{i,j}+bx_{i,j}^3=0$$

Here $x_{i,j}$ represents the i^{th},j^{th} oscillator of the network corresponding to the i^{th},j^{th} pixel of the image. The network of oscillators corresponds to the number of pixels of the underlying image, i.e. for one pixel we have one oscillator. It means, for example if we have an image of size 100 X 100 pixels then we handle this image with a network of 100 X 100 oscillators. It is worth mentioning here that in the case of contrast enhancement, the network of oscillators must be uncoupled and not coupled. This is because we want to increase (decrease) the difference at pixel level. A coupled network of oscillator is preferably used for image segmentation discussed in the next section.

Here we present a detailed example of contrast enhancement operation performed on a low contrasted image by using a network of Duffing oscillators represented in eq(2).

Fig.2a

Input image

Fig.2b

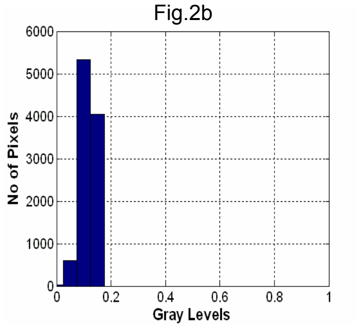


Fig.2c

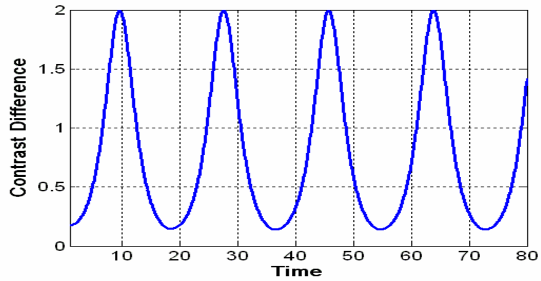


Fig.3a

t = 3.6

Fig.3b

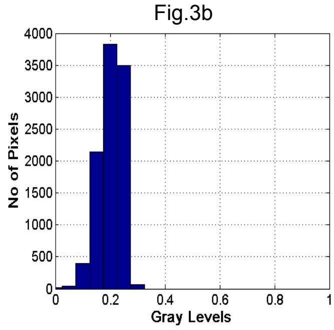


Fig.4a

t = 4.8

Fig.4b

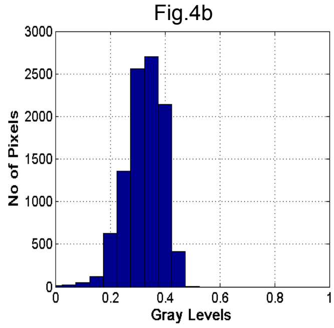


Fig.5a

t = 6

Fig.5b

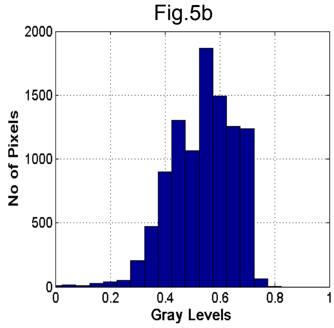


Fig.6a

Optimum output

Fig.6b

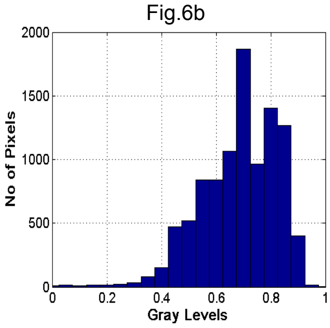


Fig.2a shows an input image with initial histogram Fig.2b of its gray-levels indicates a very weak contrasted image. Fig. 2b shows that initially at t=0, all of the gray-levels of the input image lie within 0 and 0.2. To enhance the contrast of the image these limits should be widened. This is what nonlinear oscillator network exactly does. Given an image, the network increases and decreases the contrast of the image over time. This behaviour is periodic in nature. The image when submitted to the oscillatory network then it follows the dynamics of the the network. The initial gray-levels act as initial conditions for the corresponding oscillators. Each oscillator handles its own pixel independently. Fig.2c shows how the contrast of the input image evolves over time. We selected some results at different time steps to show how the contrast increases gradually. Fig.3a represents the status of image contrast noted at t=3.6 with an increased gray-level axis shown in Fig.3b. At t=4.8, the visibility becomes more clear accompanied with a better gray-level histogram as shown in Fig.4a and Fig.4b respectively. Later at t=6 the same trend continue to grow positively as depicted in Fig.5a and Fig.5b. At t=6.6, the most optimum result is observed. Here gray-level axis indicates that the contrast is now almost spanned over the whole axis and a much clear image Fig.6a is obtained. A remarkable increase in the contrast can be observed between Fig.2a and Fig.6a.

It is clearly visible that contrast enhancement operation undergoes a periodic evolution. We should look for optimal results only as long as contrast-difference curve holds positive value because the image inverts itself when the curve has negative value. The exact phases of the oscillator network having optimum results depends on the initial condition, i.e. input image and constants a and b.

Fig.7a contains an input image with corresponding gray-level histogram in Fig.7b. This image has similar initial gray-level range as of image Fig.2a. The behaviour of the oscillator network for this image is found to be the same as it is with Fig.2a. Fig.7c and Fig.7d show an optimum output image with a much spanned gray-level histogram.

Fig.8a shows how the dynamics of the contrast-difference curve evolve over time if the input image has an initial contrast slightly different to Fig.2a and Fig.7a. The input image Fig.8b now has initial gray-levels within 0.2 and 0.4 as its histogram Fig.8c shows. An optimum output image is shown in Fig.8d with a scaled histogram Fig.8e.

For input image Fig.9b, we have initial gray-levels within 0.6 and 0.8 as depicted in Fig.9c. To generate an optimum result we used the following parameters for oscillatory network, i.e. a=-0.05 and b=0.5. Fig.9a reveals how the contrast varies over time with this set of parameters. Fig.9d and Fig.9e show an optimum image output and enhanced image histogram respectively. It is observed that for different images having the same initial gray-level range, the oscillatory network exhibit the same dynamics for all images under constant network parameters a and b.

Fig.7a

Input image

Fig.7b

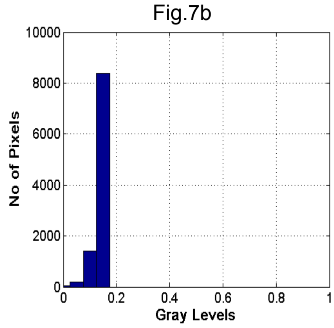


Fig.7c

Optimum output

Fig.7d

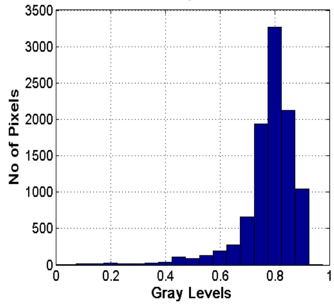


Fig.8a

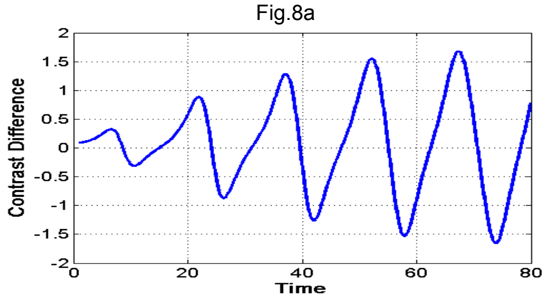


Fig.8b

Input image

Fig.8c

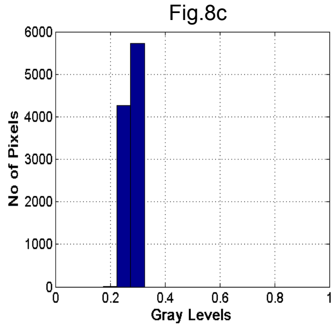


Fig.8d

Optimum output

Fig.8e

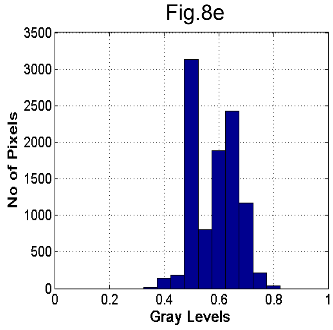


Fig.9a

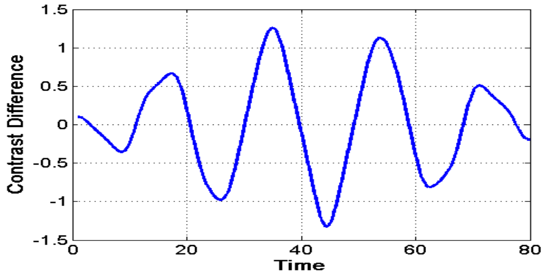


Fig.9b

Input image

Fig.9c

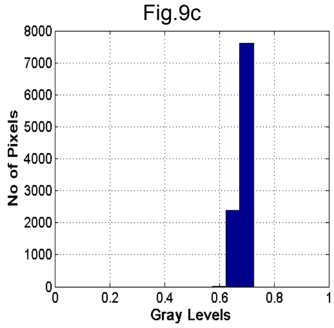


Fig.9d

Optimum ouput

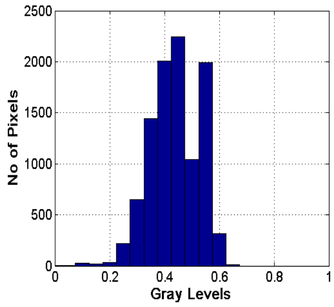


Fig.10a

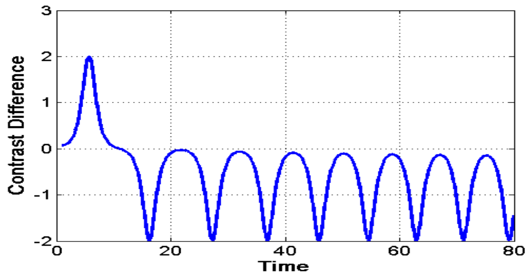
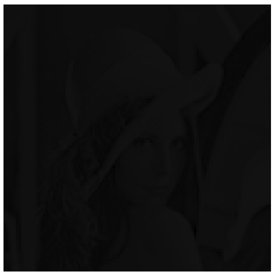


Fig.10b



Input image

Fig.10c

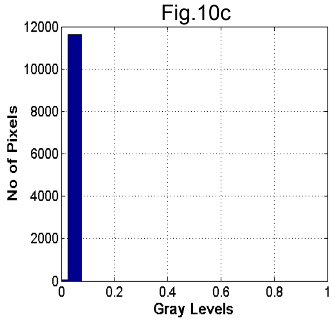
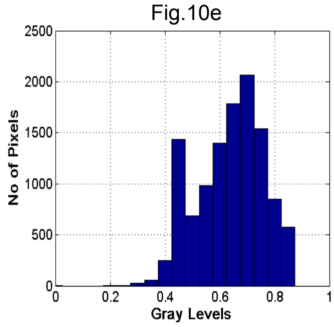


Fig.10d

Optimum output

Fig.10e



2.2. The Van der Pol-Duffing Oscillator

For image contrast enhancement operations, we also tested a nonlinear oscillator designed as a combination of Duffing and Van-der-pol oscillators. The following nonlinear 2nd order differential equation controls the dynamics of this joint-oscillator.

$$\frac{d^2x}{dt^2} + ax + bx^3 - \varepsilon\left(1 - x^2\right)\frac{dx}{dt} = 0 \qquad (3)$$

Where 'x' is the amplitude and a, b, ε are constants.
For an uncoupled network of this type of oscillators, eq(3) takes the form as given under.

$$\frac{d^2x_{i,j}}{dt^2} + ax_{i,j} + bx_{i,j}^3 - \varepsilon\left(1 - x_{i,j}^2\right)\frac{dx_{i,j}}{dt} = 0 \qquad (4)$$

Where $x_{i,j}$ represents the i^{th},j^{th} oscillator of the network corresponding to the i^{th},j^{th} pixel of the underlying image. The working principle for this oscillator is also the same as Duffing oscillator described in sec-2.1. We tested this oscillator especially for images having very low initial contrast, i.e. almost close to zero. Some good results with interesting dynamic behaviour are presented.
Fig.10b and Fig.11b show two different images but with initial gray-levels in the same range as shown in Fig.10c and Fig.11c. The network performs the same contrast evolution for both images as depicted in Fig.10a and Fig.11a. In both cases the network leads the contrast up to a certain maximum value and then creates variations in the contrast periodically below zero. The optimum contrast in both images is observed only before the first positive maxima of the contrast-difference curve. For image Fig.12d, we use the following network parameters to get an optimum result: a=-0.5, b=0.2, ε=0.01.

Fig.11a

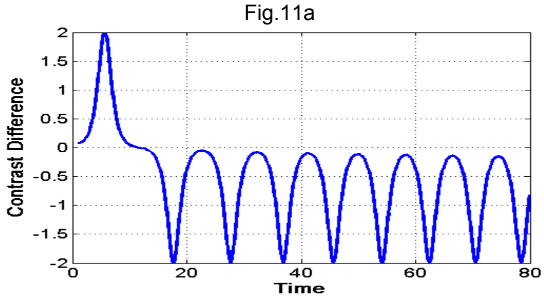


Fig.11b

Input image

Fig.11c

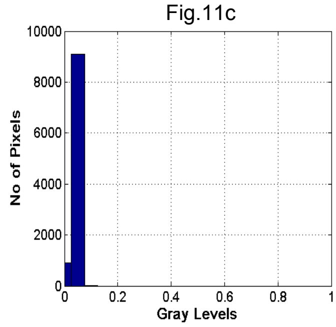
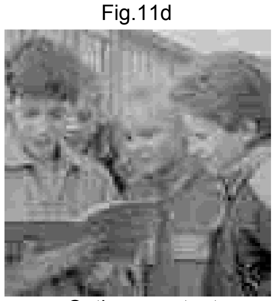


Fig.11d



Optimum output

Fig.11e

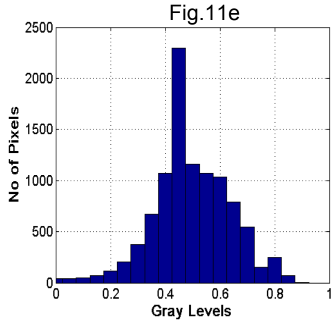


Fig.12a indicates that in this case the amplitude of the oscillations decreases over time.

Fig.12a

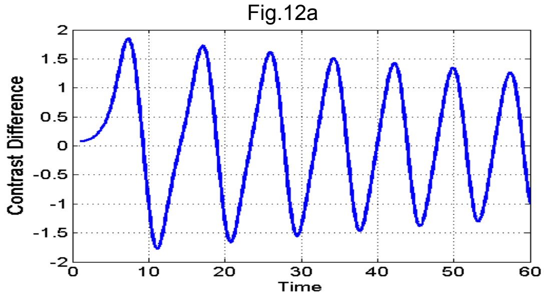


Fig.12b

Input image

Fig.12c

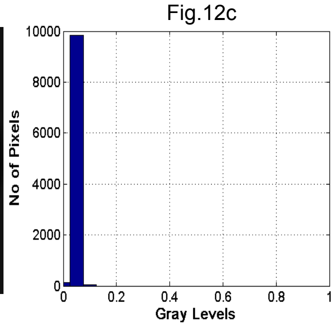
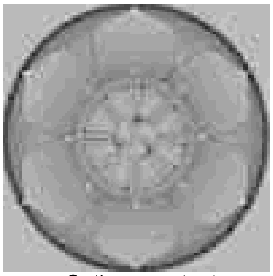
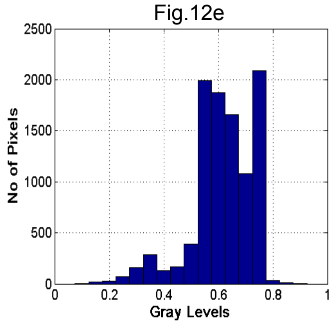


Fig.12d



Optimum output

Fig.12e



3. Conclusions

In this paper, we discussed two uncoupled network models based on nonlinear oscillators for image contrast enhancement operations. The basic element of one model is a classical Duffing oscillator with double well potential whereas Van der pol-Duffing oscillator constitutes the core of the other nonlinear network model. Acceptable results are generated through both models proving the efficiency of nonlinear-oscillator based networks for image contrast enhancement operations. Some further image processing operations, e.g smoothing, noise removal etc can be used to sharpen the quality of the obtained results. The results are highly dependent on the initial conditions which require a careful selection of network parameters to achieve useful results. At present there is no systematic way to choose these parameters. A systematic analytical study of these oscillator-based networks may provide a high degree of control over these networks. This study will provide a way to define an effective range of network parameters to get good results from the network. Further, based on this strong analytical theory, a uniform oscillator network may also be searched which can perform multiple tasks just by the suitable selection of network parameters. These multiple tasks may include edge detection, image segmentation and image contrast enhancement etc.

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