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Robust contrast enhancement by a coupled oscillatory paradigm

An application for visual sensors in transportation

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Abstract

Purpose – An image contrast enhancement is one of the most important low-level image pre-processing tasks required by the vision-based advanced driver assistance systems (ADAS). This paper seeks to address this important issue keeping the real time constraints in focus, which is especially vital for the ADAS.

Design/methodology/approach – The approach is based on a paradigm of nonlinear-coupled oscillators in image processing. Each layer of the colored images is treated as an independent grayscale image and is processed separately by the paradigm. The pixels with the lowest and the highest gray levels are chosen and their difference is enhanced to span all the gray levels in an image over the entire gray level range, i.e. [0 1]. This operation enhances the contrast in each layer and the enhanced layers are finally combined to produce a color image of a much improved quality.

Findings – The approach performs robust contrast enhancement as compared to other approaches available in the relevant literature. Generally, other approaches do need a new setting of parameters for every new image to perform its task, i.e. contrast enhancement. This limitation makes these approaches not to be useful for real-time applications such as ADAS. Whereas, the proposed approach presented in this paper performs contrast enhancement for different images under the same setting of parameters, hence giving rise to the robustness in the system. The unique setting of parameters is derived through a bifurcation analysis explained in the paper.

Originality/value – The proposed approach is novel in different aspects. First, the proposed paradigm comprises of coupled differential equations, and therefore, offers a continuous model as opposed to other approaches in the relevant literature. This continuity in the model is an inherent feature of the proposed approach, which could be useful in realizing real-time image processing with an analog implemented circuit of the approach. Furthermore, a novel framework combining coupled oscillatory paradigm and cellular neural network is also possible to achieve ultra-fast solution in image contrast enhancement.

Keywords Oscillators, Transportation

Paper type Research paper

1. Introduction

Contrast enhancement is one of the most important and widely studied research areas in the field of images or machine vision. The issue has been addressed from multiple orientations, e.g. medical, photography, real-time applications, de-noising, etc. A review of the state of the art reveals that mostly the focus of the researchers has been the contrast enhancement of the grayscale images, but not the colored images, although a color image may provide much more useful information for further processing than a simple grayscale image. The reason was that the use or importance of the machine vision was not widely realized until late 1990s. Owing to this, we can now find some

COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering
Vol. 30 No. 4, 2011
pp. 1417-1433

0332-1649
DOI 10.1108/03321641111133299

remarkable contributions regarding to the color-image contrast enhancement presented during the last few years. Here is a brief summary of this notable research work followed by some pros and cons of this state of the art.

Starck *et al.* (2003) purposed an image contrast enhancement technique based on the curvelet transform. The approach is valid both for the grayscale as well as for the color images. Basically, the curvelet transform has been used for image de-noising and not specifically for the contrast enhancement. Owing to this characteristic of the curvelet transform, the approach removes and/or minimizes the image noise considerably, but improves the contrast a little. Tsai and Yeh (2008) used HSV color model and a piece-wise linear function for the contrast enhancement. The image is first required to be smoothed by using the Gaussian smooth function. Peaks and valleys are calculated in the image luminance histogram which are then used to automatically adjust the number of the line segments in the piece-wise linear function. The approach requires two transformations, i.e. from RGB to HSV and then after processing, from HSV to RGB. It is easier to work with the HSV color model, but regarding to the contrast enhancement, the experiments showed that the processing based on RGB color model, produce better results. Provenzi *et al.* (2008) also proposed a HSV color model-based technique which is derived by combining two color correction algorithms, i.e. random spray retinex (RSR) and automatic color equalization (ACE). The approach is given the name as RACE. The positive aspects of both schemes (RSR and ACE) are brought together and the drawbacks of each scheme are removed in their joint-shape (RACE). The key objective of the RACE technique is similar to its predecessors, i.e. color correction and not the contrast enhancement. This requires an input image with sufficient amount of initial contrast, which obviously may not be the case in a real dynamical environment. Lin *et al.* (2009) used a YUV color model for contrast enhancement. The method comprises of two main stages, i.e. the iterative sub-histogram equalization and the fine-tuning of the resulted histogram. The first stage, implements a classical brightness-preserving bi-histogram equalization approach in an iterative way until the brightness mean converges to a reasonable value. In the second stage, the fine-tuning of the resulted histogram solves the quantization issue, which is generated during the first stage. In general, the YUV color space provides compressed data values, hence is found to be less accurate as compared to a generic RGB color space. Park *et al.* (2008) proposed a method using dynamic range separate histogram equalization. They used weighted average of the absolute color difference to get more detailed histogram. However, the main concern of this approach was to prevent color distortions. Xiao and Ohya (2007) used HSV model and applied wavelet transforms on the "V" component only. The decomposition of "V" components results into the approximate components and the detail components. A simple contrast enhancement method is applied on the approximate components and then an inverse wavelet transform is applied to reconstruct the brightness information. The "S" components are also improved by histogram equalization whereas the "H" components are not changed. The authors accept that the improvement of the detail components may also be effective. A relationship between "V" and "S" components is not well defined. Under very low lighting conditions, the "H" components may also need to be improved which is not considered in this approach. Sun *et al.* (2005) proposed an approach for contrast enhancement which is based on the histogram specification. It extracts the differential information from the input histogram and applies some extra parameters to achieve good contrast. The method works well with the images having a considerable amount of initial contrast so that it can get key data from the histogram of the input image to improve it. Meylan and Süsstrunk (2004) proposed an approach which is based on classical retinex-theory. The approach is computationally expensive as each pixel goes through an adaptive filter in a sequence. Further, the filter is applied only on the luminance component of the image leaving the hue and saturation layers without any processing. Munteanu and Rosa (2001) presented a method for color image enhancement using genetic algorithm. The multi-scale retinex with color restoration (MSRCR) model is made adaptive for each image by using real-coded GA. The GA finds the set of parameters for the MSRCR model to be applied on the input images. For real-time applications, this approach does not seem to be feasible. Also, it requires prior information of the input image before its processing, which is not possible for applications designed to run into a dynamic environment. Duan and Qiu (2004) proposed an HSI model-based color-image enhancement. The quality of the enhanced image depends on one control parameter and no way is defined to set an optimized value for this parameter automatically. Further, a tradeoff has to be set between the computational time and the quality of the output images.

The above brief review shows that in most of the approaches, the contrast enhancement of the colored images is made through the HSV/HSL color spaces. These color spaces are derived from the classical color space RGB. It is easy to work with these models as these present the colors in terms of hue, saturation and brightness/luminance. Generally, the enhancement algorithms are applied only on the brightness or luminance, i.e. "V" or "L" layers, but this does not solve the problem as varying only "V" or "L" layers has a strong affect on "H" and "S" layers which hold the color and the saturation information. This can lead to the false colored contrast enhancement. Also, the images which are taken under very low light conditions, e.g. night, fog, etc. require their "H" layer also to be improved. This issue is not addressed in these approaches.

In this paper, we present a new approach for the contrast enhancement of colored images based on a paradigm of nonlinear oscillators. The paradigm has already been successfully used for enhancing the contrast of grayscale images (Kyamakya *et al.*, 2010). We used the most generic color space model in our approach, i.e. the RGB color space. The RGB model has a close relation with the human color vision system than its derived versions, i.e. HSV/HSI, etc. The rest of the paper is organized as follows. Section 2 briefly describes the RGB model and its close connection with the human visual system in general. Section 3 provides an in-depth analytical study of our proposed oscillatory paradigm. The results achieved are presented in Section 4. Section 5 describes an integrated system comprising of coupled oscillatory paradigm and cellular neural networks, and Section 6 contains concluding remarks.

2. How is the color perceived?

Color vision is perceived due to the presence of different radiations having well-defined frequency/wavelength ranges, all originating from a single light source, e.g. sunlight. It means that the "light" in its true nature is a composite of different radiations. So, when the light falls on an object, then based on some physical properties of that object, different radiations get different responses. Some radiations are absorbed by the object but some not. The radiations that are not absorbed are actually reflected back by the object. If those reflected radiations are a part of the visible spectrum, then our eyes can perceive them as a color of that particular object (Figure 1).

Theory of trichromacy (Hernandez, 2002), as proposed by Thomas Young, has bridged the gap between the visible-spectrum phenomenon and the human-eye color-perceiving process (Figure 2). The theory was also proven later by Hermann von Helmholtz (Hernandez, 2002) and Gunnar Svaetichin (1956) both physiologically and experimentally. This theory reveals that the human-eye contains three different types of photoreceptor cells in which each type is sensitive to a specific wavelength of the light, i.e. the visible spectrum. These photoreceptor cells are called as the cone cells. There are about six million cone cells in each eye. Based on the sensitivity/response of the cone cells to the three different wavelengths of the light, the cone cells are usually labeled as short (S), medium (M), and long (L), and also referred to as blue, green, and red cones. Besides the theory of trichromacy, the theory of opponent process (Hurvich and Jameson, 1974) is also well respected to get the full understanding of the color-vision process. This theory states that although the cone-cells have different peak frequencies, but the three wavelengths of the light are strongly overlapped. So, a range of frequencies may stimulate two/three cone cells to respond at the

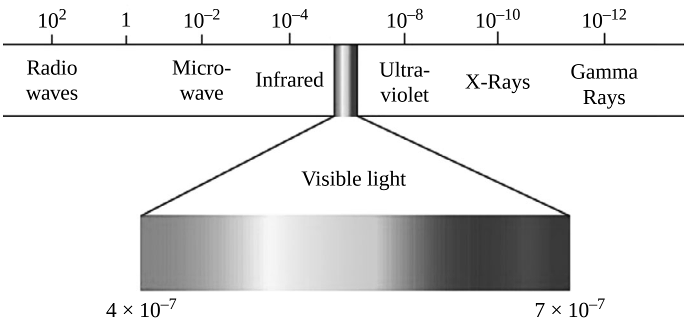

Figure 1.
Visible spectrum

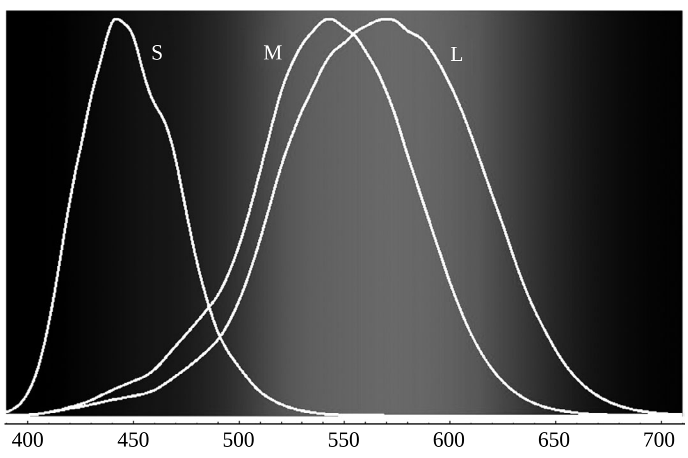

Figure 2.
Normalized response of human cones to the light of different wavelengths

same time. This makes our visual system to detect the difference between the responses of the cone cells. This difference is actually sent to the brain as a signal, which processes the signal to perceive a real color.

The *RGB* color model is based on the trichromacy theory and it offers a wide range of colors as opposed to the *HSV*/HSI color models which offer a single dimension of color. If the values of all the three layers in the *RGB* model, i.e. the R layer, the G layer, and the B layer, are carefully adjusted with each other for a particular image, then the image will offer a better visibility as compared to its *HSV*/HSI counterparts.

3. Paradigm of the nonlinear oscillators

We use a paradigm (1a) and (1b) of nonlinear oscillators to perform the contrast enhancement of the *RGB*-colored images. The paradigm comprises of two well-known nonlinear oscillators coupled together, i.e. van der Pol and Duffing oscillator:

$$\frac{d^2x}{dt^2} - \varepsilon_1(1 - x^2)\frac{dx}{dt} + \omega_1^2 x = c_1 y + c_2\frac{dy}{dt} \tag{1a}$$

$$\frac{d^2y}{dt^2} + \varepsilon_2\frac{dy}{dt} + \omega_2^2 y + c_0 y^3 = c_3 x + c_4\frac{dx}{dt} \tag{1b}$$

where c_1 and c_3 are the elastic coupling parameters, c_2 and c_4 are the dissipative coupling parameters, x(t) and y(t) represent the solutions of the coupled oscillators. The stability of the equilibrium points is carried out by restricting our analysis to the following case: $c_1 = c_3$, $c_2 = c_4 = 0$, $\omega_1 = \omega_2$. From equations (1a) and (1b), we obtain the following equilibrium points:

$$P_1\left(\sqrt{\frac{c_1^2(c_1^2 - \omega_1^2\omega_2^2)}{c_0\omega_1^6}},\quad 0\quad \sqrt{\frac{c_1^2(c_1^2 - \omega_1^2\omega_2^2)}{c_0\omega_1^2}},\quad 0\right) \tag{2a}$$

$$P_2\left(\sqrt{\frac{c_1^2(c_1^2 - \omega_1^2\omega_2^2)}{c_0\omega_1^6}},\quad 0,\quad -\sqrt{\frac{(c_1^2 - \omega_1^2\omega_2^2)}{c_0\omega_1^2}},\quad 0\right) \tag{2b}$$

$$P_3\left(-\sqrt{\frac{c_1^2(c_1^2 - \omega_1^2\omega_2^2)}{c_0\omega_1^6}},\quad 0,\quad \sqrt{\frac{c_1^2 - \omega_1^2\omega_2^2}{c_0\omega_1^2}},\quad 0\right) \tag{2c}$$

$$P_4\left(-\sqrt{\frac{c_1^2(c_1^2 - \omega_1^2\omega_2^2)}{c_0\omega_1^6}},\quad 0,\quad -\sqrt{\frac{c_1^2 - \omega_1^2\omega_2^2}{c_0\omega_1^2}},\quad 0\right) \tag{2d}$$

We also obtain a critical equilibrium point $P_c(0, 0, 0, 0)$. The stability of the above equilibrium points can be investigated by rewriting equations (1a) and (1b) in the following form:

$$\frac{dx}{dt} = v \tag{3a}$$

$$\frac{dv}{dt} = \varepsilon_1(1 - x^2)v - \omega_1^2 x + c_1 y \tag{3b}$$

$$\frac{dy}{dt} = z \tag{3c}$$

$$\frac{dz}{dt} = -\varepsilon_2 z - \omega_2^2 y - c_0 y^3 + c_1 x \tag{3d}$$

and linearizing around a given equilibrium state (x_0, v_0, y_0, z_0) to obtain the Jacobian matrix M_j:

$$M_J = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\omega_2^1 - 2\varepsilon_1 X_0 V_0 & \varepsilon_1\left(1 - x_0^2\right) & c_1 & 0 \\ 0 & 0 & 0 & 1 \\ c_1 & 0 & -\omega_2^2 - 3c_0 y_0^2 & -\varepsilon_2 \end{bmatrix} \tag{4}$$

The eigenvalues of the Jacobian matrix M_j are the solutions of equation (5):

$$a_0\lambda^4 + a_1\lambda^3 + a_2\lambda^2 + a_3\lambda + a_4 = 0 \tag{5}$$

where the coefficients $a_m(m = 0, 1, 2, 3, 4)$ are defined as follows:

$$a_0 = 1 \tag{6a}$$

$$a_1 = \varepsilon_2 - \varepsilon_1\left(1 - x_0^2\right) \tag{6b}$$

$$a_2 = \omega_1^2 + \omega_2^2 + 2\varepsilon_1 X_0 V_0 + 3c_0 y_0^2 - \varepsilon_1\varepsilon_2\left(1 - x_0^2\right) \tag{6c}$$

$$a_3 = \varepsilon_2\left(\omega_1^2 + 2\varepsilon_1 X_0 V_0\right) - \varepsilon_1\left(1 - x_0^2\right)\left(\omega_2^2 + 3c_0 y_0^2\right) \tag{6d}$$

$$a_4 = \left(\omega_1^2 + 2\varepsilon_1 X_0 V_0\right)\left(\omega_2^2 + 3c_0 y_0^2\right) - c_1^2 \tag{6e}$$

A deep analysis is performed based on Routh-Hurwitz theorem and the bifurcation theory to derive the necessary conditions to ensure the stability of the equilibrium points. In the bifurcation analysis, we used the parameter c_1 as a control parameter. The analysis reveals three different possible states of the system. The first state is the quenching state (i.e. the death of oscillations). The second one is the state of equilibrium and the last one is the oscillatory state. The system exhibits its quenching state when the critical equilibrium point $P_c(0, 0, 0, 0)$ is stable. The critical equilibrium point is found stable under the following relationships:

$$\varepsilon_1 < \varepsilon_2 \tag{7a}$$

$$\omega_1\sqrt{\varepsilon_1\varepsilon_2} < c_1 < \omega_1^2 \tag{7b}$$

The non-zero equilibrium points $P_i(i = 1, 2, 3, 4)$ are stable under the following relations:

$$\varepsilon_1 < \varepsilon_2 \tag{8a}$$

$$c_1 > \omega_1^2 \tag{8b}$$

The system remains in the oscillatory phase under the following conditions:

$$\varepsilon_1 < \varepsilon_2 \tag{9a}$$

$$0 < c_1 < \omega_1\sqrt{\varepsilon_1\varepsilon_2} \tag{9b}$$

The next section is concerned with the numerical study aiming at verification of the analytical results.

4. Numerical study

4.1 SIMULINK-based model

We first present a SIMULINK-based model (Figure 3) of the paradigm (1a) and (1b) and provide a validation of the analytical relations established in the previous section. The model examines the paradigm (1a) and (1b) from the perspective of classical nonlinear dynamics without involving image contrast enhancement. Figure 4 shows a graph drawn between the van der Pol solutions, i.e. x and the control parameter c_1. The following settings of parameters are used: $\varepsilon_1 = 0.4$, $\varepsilon_2 = 1$, $\omega_1 = 1$, $\omega_2 = 1$, $c_2 = 0$, $c_4 = 0$, $c_0 = 0.5$, $c_1 = c_3$. The control parameter c_1 is varied between 0.35 and 1.3, to observe all the three possible states of the paradigm. The graph clearly verifies the analytical relations derived in the previous section.

For all $c_1 <= 0.6$, all of the x-solutions of the paradigm (1a) and (1b) lie exactly on one vertical line. This is due to the fact that the paradigm (1a) and (1b) is in the oscillatory state which coincides with the relation equations (9a) and (9b) derived above. The height/length of each vertical line shows the maximum and minimum amplitudes of the oscillations against different values of c_1. Under the above parameters' values, the paradigm (1a) and (1b) should be in the quenching state for $0.6 < c_1 < 1$ satisfying the relation equations (7a) and (7b). This is also perfectly matched as shown in Figure 4. All the x-solutions are concentrated on zero, i.e. all the oscillations are damped in this domain. For $c_1 >= 1$, the paradigm (1a) and (1b) enters into the non-zero equilibrium state, satisfying the relation equations (8a) and (8b). In this domain, all the x-solutions are concentrated on different non-zero positive point for different values of c_1.

4.2 How is the contrast enhancement achieved?

A gray-scale image is regarded as a well-enhanced image if all of its gray-levels are spanned over the entire intensity range, i.e. between 0 and 1. Here, "0" represents the black and "1" represents the white. The paradigm (1a) and (1b) has the ability to perform this spanning in two of its three states described above, i.e. the oscillatory state and the non-zero equilibrium state. We prefer the non-zero equilibrium state to perform contrast enhancement because in this state, an automatic way to select the best-enhanced image is sure, making the overall approach more robust. Figure 5 shows the x-solutions (i.e. van der Pol) of the paradigm (1a) and (1b) against a simple real-valued interval of [0 1]. The following setting of parameters is used: $\varepsilon_1 = 0.4$, $\varepsilon_2 = 1$, $\omega_1 = 1$, $\omega_2 = 1$, $c_2 = 0$, $c_4 = 0$, $c_0 = 0.5$, $c_1 = c_3 = 1.15$. It can be observed that for the real-values on the *x*-axis lying in the range of 0 to 0.15 (approx.), the x-solutions are spanned over [0 1]. For the real-values greater than 0.15, the x-solutions of the paradigm produce a continuous

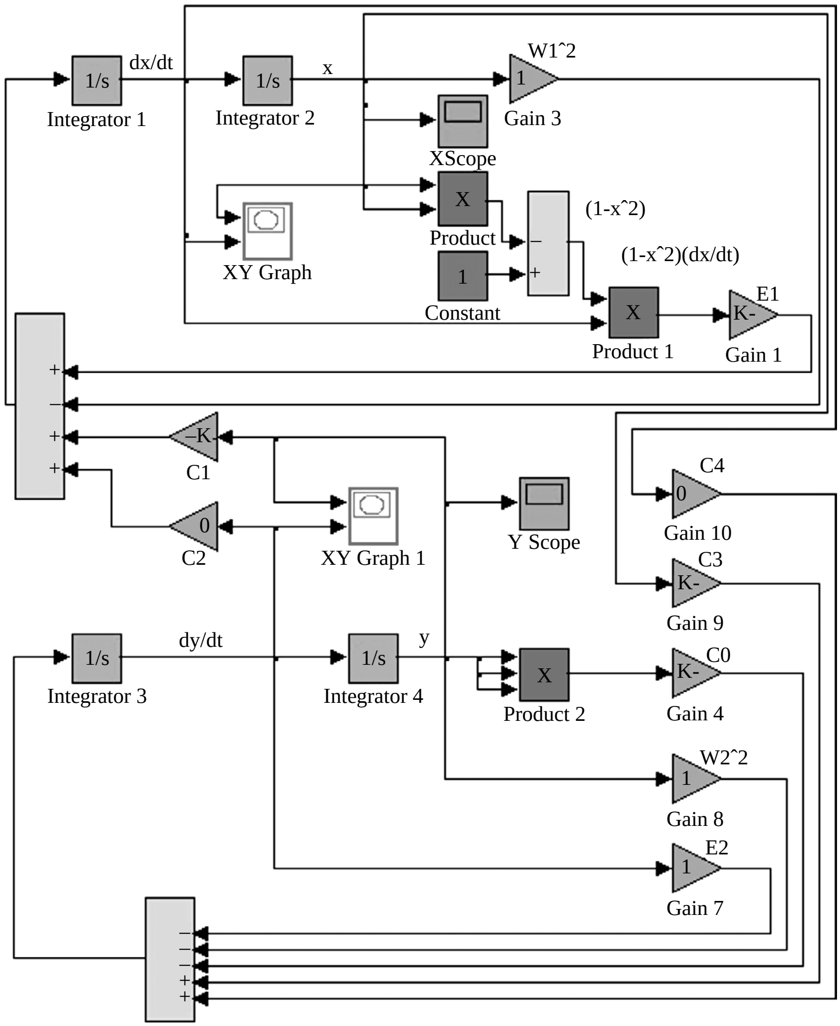

Figure 3.
SIMULINK-based model of the paradigm (1a) and (1b)

line, i.e. all the x-solutions converge to some positive value. This is due to the fact that the system is working in a non-zero equilibrium state and for the real-values greater than 0.15 on the *x*-axis, the x-solutions show the convergence of the system. If the system is permitted to process over a long time, then all of the real-values on the x-axis show a definite convergence as shown in Figure 6 except the value of zero. That shows the sensitivity of the system for those real-values of the interval [0 1], which are very close to zero. Based on this analysis, we will always rescale our input image on a range that is close to zero. This rescaling of the input image always produces a good enhanced image regardless of the initial gray-levels of the input image. To make sure that we always get an output range, which is well-spanned over [0 1], we select two specific real-values in the

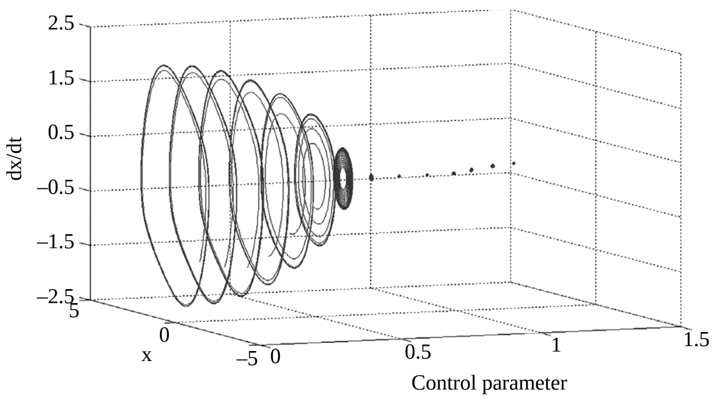

Figure 4.
Bifurcation diagram

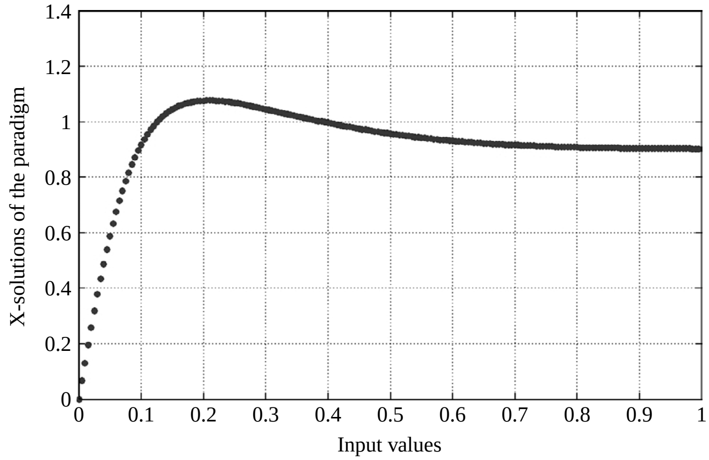

Figure 5.
Spanning of x-solution for $t = 0$ to 10

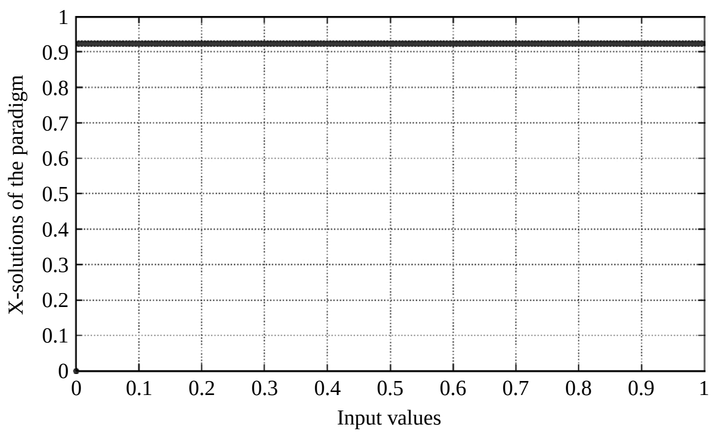

Figure 6.
Spanning of x-solution for $t = 0$ to 100

input range such that the selected values represent the minimum and maximum values of the input real-value range. The output range will be well-spanned over [0 1] if the difference between those specific values is maximum, i.e. 1. The same analogy can be realized in the case of real-images. In a grayscale image, all the gray-levels take the range between 0 and 1. The low-contrasted images can be enhanced using the methodology described above. The two specific pixel-positions having the minimum and the maximum values in the input image are noted, and the difference is tracked. If the difference is maximum, i.e. 1, the processing is stopped. At that point, all the gray-levels are well-spanned over the whole range [0 1], hence presenting a good differentiable visibility.

4.3 MATLAB-based model for image contrast enhancement

The proposed coupled oscillatory system consists of two nonlinear oscillators, i.e. a van der Pol oscillator and a Duffing oscillator, each represented by a second-order nonlinear differential equation as given in equations (1a) and (1b). In general, this paradigm requires just four one-dimensional inputs as its initial conditions to achieve a solution. To use this paradigm for image processing, i.e. contrast enhancement, the initial conditions must be set according to the actual pixel values and the size of the input image. Now corresponding to each pixel, we do need to set four initial conditions, i.e. the position and the velocity for van der Pol oscillator, and, the position and the velocity for the Duffing oscillator. We treat our input image as one complete vector where the elements of this vector represent the actual pixel values of the image. To cope with all the four mandatory initial conditions required for each pixel, we develop four vectors each having the same size as of input image. Two vectors will be used to hold the position values of all the pixels and the other two vectors will hold the velocity values of all the pixels. With this methodology, each pixel has its four initial conditions given at the specific locations of all the four vectors. The schematic diagram of the approach is shown in the Figure 7. Generally, the input image is loaded in the x or/and y vectors, i.e. the position vectors. The optimum solution of this processing, which is an enhanced image in this case, is also retrieved through x- or y-position vectors. As the solution comes in a vector form, so we do need to perform a reshape operation on that processed vector image to produce a grid-like form of the output image.

The framework shown in Figure 7, works well with the *RGB* colored images. As the *RGB* images contain three different channels to hold color information, each channel has to be improved separately. The approach is simple and straightforward. All the three channels, i.e. R, G, and B are extracted from the input *RGB* image, these channels are submitted separately to the paradigm (1a) and (1b) as shown in Figure 7. The paradigm (1a) and (1b) improves the contrast in each channel. Finally, all these improved channels are joined together to give rise to a much better color image. The worth-mentioning advantage of the proposed approach is that the initial pixel values, of each channel, serve as initial conditions for the paradigm (1a) and (1b). Owing to this methodology, although the contrast in each channel is enhanced, the synchronization among different channels is preserved/improved in terms of color. Figure 8 shows a detailed example. The simulation parameters are: $\varepsilon_1 = 0.4$, $\varepsilon_2 = 1$, $\omega_1 = 1$, $\omega_2 = 1$, $c_2 = 0$, $c_4 = 0$, $c_0 = 0.5$, $c_1 = c_3 = 1.15$.

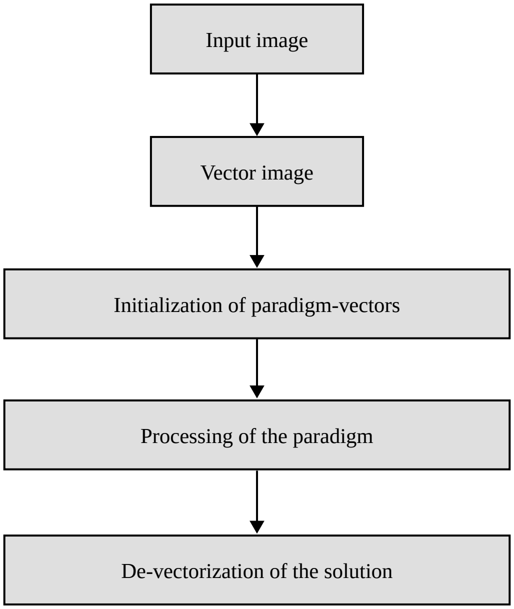

Figure 7. MATLAB-based schematic model of the paradigm (1a) and (1b)

A comparison of the results through the paradigm (1a) and (1b) against two well-known contrast enhancement techniques, i.e. histogram equalization and adaptive histogram equalization, is shown in Figures 9 and 10.

5. Integration of CNN with coupled oscillatory paradigm

The prime features reflected by a CNN paradigm include, local connectivity, parallel computing, first-order ODE modeling and use of filters in the form of classical convolution operations for images. These characteristics are enough to present this paradigm as an ideal platform to perform different image-processing tasks. Nevertheless, as described above, the key limitation with CNN is the lack of template optimization techniques. The reason for this limitation lies in the classical mandatory supervised training/learning process used to determine the templates. Owing to this, the templates obtained are optimal for the test images only. These templates cannot be optimal for images experiencing temporal and/or spatial dynamics. On the other hand, coupled oscillatory approach has been proved to be robust one to the dynamic variations in the contrast of the input images and do not require any parameter optimization for different images during the course of processing. This prime characteristic is achieved through an offline bifurcation analysis, which reveals an appropriate setting of parameters for the coupled system. This led us to propose a hybrid computing architecture for image processing that will combine the strong points of both CNN and the coupled nonlinear oscillators. The approach to calculate the appropriate templates, i.e. NAOP (Chedjou *et al.*, 2010) has been the key motivation for joining these two paradigms. According to this idea, the core processing will be the done by coupled oscillatory system. The hybrid computing architecture can be defined as a realization of the coupled oscillatory system on top of

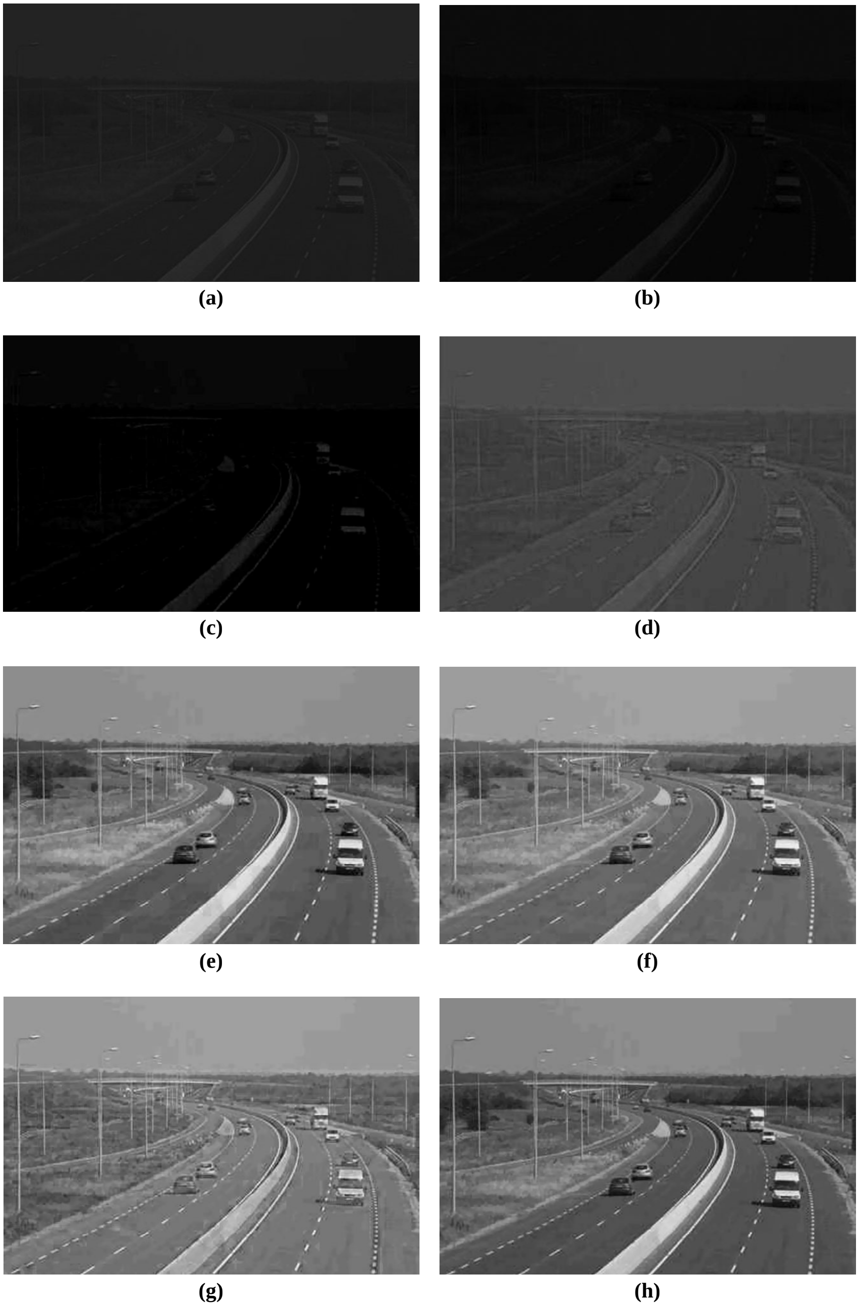

Figure 8.
(a) Input image, (b) original R-channel, (c) original G-channel, (d) original B-channel, (e) improved R-channel, (f) improved G-channel, (g) improved B-channel, (h) output image by combining all the improved channels

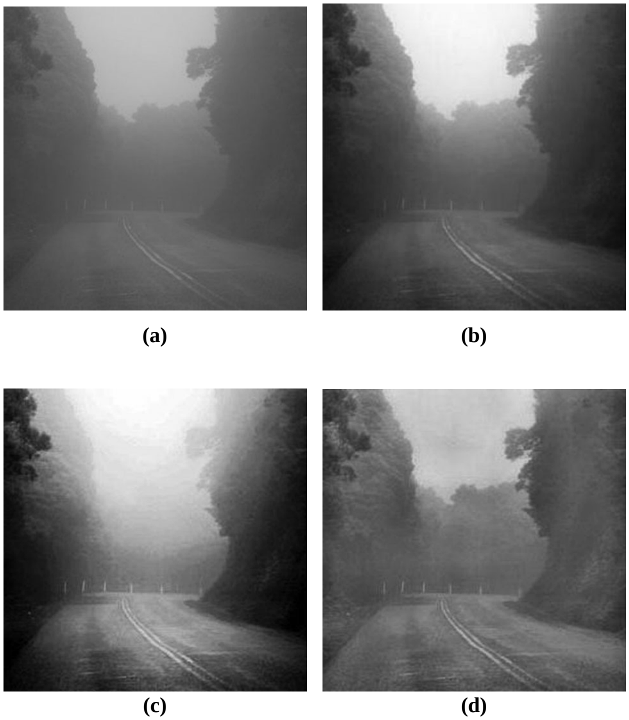

Figure 9.
(a) Input image,
(b) paradigm-I, (c) HE,
(d) adaptive HE

a cellular neural network processors framework. Hereby, the coupled oscillatory system will act as a master-system whereas the CNN processor will play the role of a slave-system used to solve, in real-time, the nonlinear ordinary differential equations describing the coupled nonlinear oscillators' model. The CNN templates could be derived through NAOP approach and later could be fed into the corresponding CNN model of the coupled oscillatory system to achieve real time processing. The hybrid approach has the following key characteristics:

- The approach is not sensitive to the dynamic changes in the contrast of the input images. This property is brought in with an offline bifurcation analysis of the coupled oscillatory paradigm which leaves the nonlinear differential equations with constant coefficients.
- The nonlinear differential equations with constant coefficients are used as one of the inputs to the NAOP technique which in turns, produce a set of CNN-templates corresponding to the differential equations. In this way, the derived templates contain the nonlinearity/dynamics of the coupled oscillatory model.
- The derived templates are then used in a CNN model to achieve real-time processing (Figure 11).

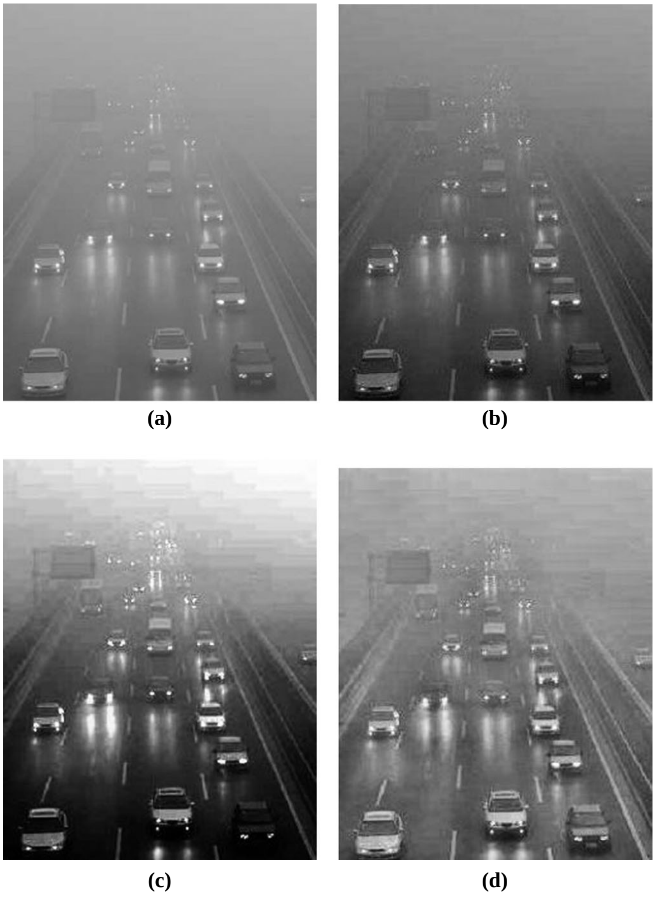

Figure 10.
(a) Input image,
(b) paradigm-I, (c) HE,
(d) adaptive HE

6. Concluding remarks

In this paper, we presented a new approach for the contrast enhancement of colored images which is based on a paradigm of nonlinear oscillators. All the three layers of the colored images are enhanced individually by the cited paradigm and then later combined. The enhancement of each layer through the oscillators does improve each layer in such a way that when the improved layers are recombined, an automatic correlation between the layers is produced which results in a good perception of the original colors. This approach produces better results as most of the existing approaches presented in literature deal only with a single layer of the colored input images, i.e. the luminous/intensity layer. The approach does therefore offer a strong potential for use in vision-based sensor of advanced driver assistance systems (ADAS). As most of the ADAS systems process only the gray-scale images and hence they do miss a key property of the scene-objects, i.e. the color. To achieve real-time processing, the proposed paradigm can be implemented on top of cellular neural networks as explained in Chedjou *et al.* (2010).

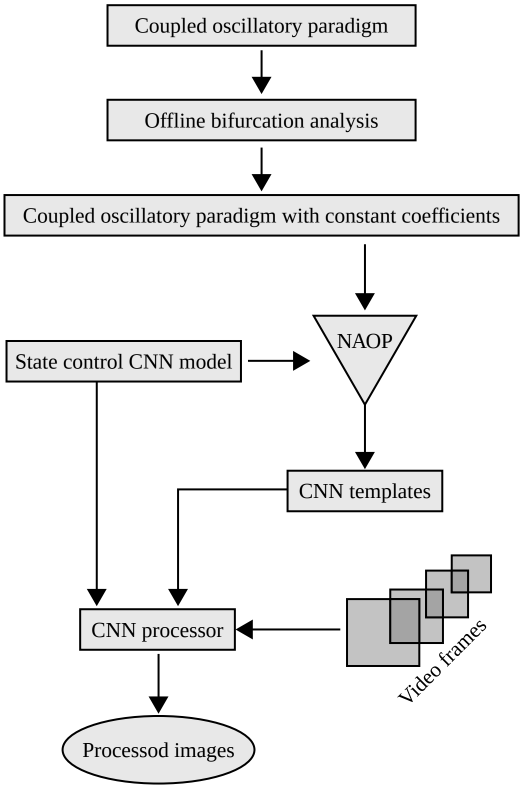

Figure 11.
A schematic architecture of an integrated system

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