On Spatial Novelty Detection via Image Contrast Enhancement using Cellular Nonlinear Networks

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Abstract – A simple contribution to spatial novelty detection in stereo-vision systems for mobile vehicles in indoor motion is presented by synthesizing a Cellular Nonlinear Network (CNN) for processing perspective images with light-dependent semantic content. Enhanced contrast images are generated by means of a fuzzy evaluation cellular subnet. Spatial novelty images can be subsequently obtained by cascading proper cellular subnets. Quality contrast evaluations are then performed on spatial novelty images using a dedicated cellular circuit. A test case is reported, to show how the suggested cellular system can provide useful information for stereo vision systems.

Key Words: - Image Contrast Enhancement, Cellular Nonlinear Network, , Circuits, Neural & Fuzzy Nets

1 Introduction

In recent years specific architectures of stereo vision systems [1] for moving vehicles have been widely developed both from the hardware point of view and from the software one [2]. On the same issues, the capabilities of Cellular Nonlinear Networks (CNNs) revealed successful for several image processing applications [3, 4]. In particular, in the case of stereo images with uncertain light-dependent content some difficulties could be faced by synthesizing CNN-based fuzzy associative memories to obtain perspective images with enhanced contrast features as in [5], but several limits still remain. In this paper a simple contribution is proposed by designing a Cellular Nonlinear Network for a progressive spatial novelty detection in mobile stereo-vision systems. For this purpose, contrast-enhanced images with respect to captured ones are firstly determined by means of a CNN-based fuzzy evaluation subsystem. Successively, spatial novelty images for supporting motion in autonomous navigation are determined by cascaded Cellular Nonlinear subnets. Feasible contrast quality evaluations are then performed [6] for the obtained spatial novelty detection results using a proper CNN-based circuit. Finally, a test case is reported, to show how the suggested cellular network could provide further information for stereo vision systems.

2 Spatial Novelty Detection Architecture

In this work a CNN-based architecture is proposed to process pairs of images of a stereo video sequence. In Fig. 1 the block diagram showing the architecture of the suggested CNN-based system is reported. After acquiring each pair of images in a stereo sequence, these images have to be separately processed in a fuzzy evaluation subnet in order to obtain two 256-gray enhanced contrast images, which present stretched histograms such that significant information is given by their lowest and highest grey levels. These images become inputs to a variation detection block for detecting variations between the generic left frame and the corresponding right one of each pair. The resulting image is a spatial novelty detection image which can probably provide further support to stereo vision systems. Finally, a 255-complement operator is inserted in the proposed architecture, with the aim of giviing a complemented code of the changing areas, if necessary. In this way, spatial novelties closest to the cameras are easily recognizable.

The suggested architecture consists in three blocks: a fuzzy evaluation subsystem, a variation detection subsystem, a 255-complement subsystem. It is important to precise that the whole architecture proposed in this paper is carried out by CNNs, being M and N equal to the

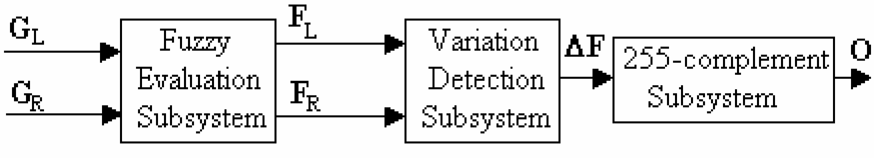

Fig. 1: Block Diagram of the proposed CNN-based architecture

numbers of rows and columns of each image to be processed. For the sake of a better comprehension, the basic notation intended for CNN is herein briefly summarized. In this paper the class of n-cell cellular neural networks is considered in the following notation [4]:

$$\begin{aligned} \dot{\boldsymbol{x}} &= -\boldsymbol{x} + \boldsymbol{T}\, \boldsymbol{g}(\boldsymbol{x}) + \boldsymbol{B}\, \boldsymbol{z} + \boldsymbol{I} \\ \boldsymbol{y} &= \boldsymbol{g}(\boldsymbol{x}) \end{aligned} \qquad (1)$$

where $\boldsymbol{x} \in \Re^n$; $\boldsymbol{y} \in \Re^n$; $\boldsymbol{z} \in \Re^n$ are the state, output, input vectors, respectively, $\boldsymbol{I} \in \Re^n$ is the vector of bias values; $\mathbf{g}(\boldsymbol{x}) \in \Re^n$ is the vector of n activation functions $g(x) = 0.5\,(|x+1|-|x-1|)$.
Moreover, the sparse matrices $\boldsymbol{T}=[T_{ij}] \in \Re^{nxn}$ and $\boldsymbol{B}=[B_{ij}] \in \Re^{nxn}$ are identified by means of their templates T and B for each synthesized CNN. In the course of the paper it is intended n = MxN for all nets forming the proposed CNN-based architecture.
The subsystems reported in Fig.1 are now separately described.

2.1 Fuzzy Evaluation Subsystem

This subsystem aims to transform captured grey images into enhanced contrast ones to be used for detecting variations between the generic left frame and the corresponding right one in a stereo vision system. This subsystem is based on two fuzzy associative memories (one per each image) designed as in [5]. In detail, images of each acquired pair of video frames are separately processed by means of two (4x4)-cell CNNs synthesized for FAMs to obtain enhanced contrast grey images, named $\mathbf{F_L}$ and $\mathbf{F_R}$.

2.2 Variation Detection Subsystem

As shown in Fig. 1, the second block of the suggested architecture consists in a Variation Detection Subsystem, which is synthesized with the aim of detecting the spatial novelties between the two enhanced contrast images $\mathbf{F_L}$ and $\mathbf{F_R}$ at the same instant. In other words, the spatial variations between frames contemporary captured by the cameras on the mobile vision system are determined. Due to the fact that captured images by stereo vision systems in indoor environments are perspective images, this operation could probably simplify the detection of the objects nearest to the cameras of the stereo-vision system during autonomous navigation. In detail, this subsystem is formed by an Inversion CNN, an Adder and an Absolute Value CNN. In particular, the Inversion CNN can be realized by an (MxN)-cell network, whose interconnection weights are given by considering the following templates of order r = 1 [7]:

$$\boldsymbol{T_1} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \boldsymbol{B_1} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \boldsymbol{I_1} = 0$$

In the same way, the Adder is realized by means of two CNNs, whose templates are:

$$\boldsymbol{T_2} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \boldsymbol{B_2} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \boldsymbol{I_2} = F_R(k\,.l)$$

$$\boldsymbol{T_3} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & -0.25 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \boldsymbol{B_3} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 2.5 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \boldsymbol{I_3} = 0$$

The output image of the Adder coincides with the input image for the subsequent CNN-based Absolute Value Subsystem, realized only by means of the following nonlinear template:

$$\boldsymbol{B_4} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & 0 \end{pmatrix} \qquad \boldsymbol{I_4} = \mathbf{0}$$

where $b = f(z_{ij})$. This subsystem gives the image named $|\mathbf{\Delta F}|$ as output image.

2.3 255-Complement Subsystem

The last block of the suggested architecture is a 255-Complement circuit. This subsystem is synthesized with the aim of computing the output image $\mathbf{O}$=O(k, l), k=1, …, M, l=1,…,N. The gray level of the (k, l)-th pixel is given by:O(k, l) = 255 - |ΔF(k, l)|. This subsystem can be considered as optional in the suggested architecture, due to the fact that it provides grey images, which could be more feasible for subsequent code steps in the vision system. The 255-Complement block can be implemented by an Inversion CNN and an Adder one. As a consequence, the corresponding CNN-based subsystem can be obtained by considering again the templates $\boldsymbol{T_1}$, $\boldsymbol{B_1}$, $\boldsymbol{T_2}$, $\boldsymbol{B_2}$, $\boldsymbol{T_3}$, $\boldsymbol{B_3}$.

3 Contrast Quality Evaluation for Spatial Novelty Images

It is well known that a feasible image quality evaluation is generally based on a measure of image contrast quality. In this work the mean absolute contrast value X_μ defined by Brendel & Roska in [6] has been considered and used as a contrast quality index for spatial novelty images. For this purpose, the value X_μ is computed by a proper CNN-based circuit, as shown in Fig. 2,

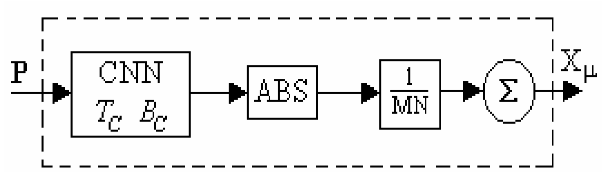

Figure 2: CNN-based system for the evaluation of X_μ

where the symbol **P** indicates a generic input spatial novelty image. The first block in the diagram is constituted by a CNN identified by the templates $\boldsymbol{T_C}$, $\boldsymbol{B_C}$ as follows:

$$\boldsymbol{T_C}=\begin{pmatrix}0 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 0\end{pmatrix} \quad \boldsymbol{B_C}=\begin{pmatrix}-0.06 & -0.06 & -0.06\\ -0.06 & 0.48 & -0.06\\ -0.06 & -0.06 & -0.06\end{pmatrix}$$

$$\boldsymbol{I}=0$$

Given a generic image **P,** this block computes a contrast map $C(k, l)$, which describes the average contrast value in the region around each pixel of the image. In detail $C(k, l)$ is a local contrast value of each pixel (k, l), k=1, ,M, l=1, ,N. Then, the calculated contrast map $C(k, l)$ contributes to computing the mean absolute contrast value X_μ, defined as[6]:

$$X_\mu = \frac{\sum_{k,l} \text{abs}\,(C(k,l))}{\text{MN}}$$

The mean contrast value $0 \le X_\mu \le 1$ can be considered as a measure of the overall quality of the input image **P**. As a consequence, if the average value is almost zero, the considered image needs to be processed to be contrast-enhanced. This will not be necessary if the mean absolute contrast value X_μ is close to a unitary value.

4 Test case

The capabilities of the designed CNN-based architecture have been investigated on several pairs of perspective images of an indoor environment stereo sequence like the selected left/right input ones reported in Fig.3. Each pair of captured images has been firstly submitted to the Fuzzy Evaluation Subsystem. In Fig.4 the enhanced contrast output images corresponding to the images in Fig.3 are shown. It can be noticed that contrast is quite enhanced in the obtained images with respect to input ones.

(a) (b)

Fig. 3: Selected pair of stereo captured images: (a) left; (b) right

(a) (b)

Fig. 4: Output enhanced contrast images of the CNN-based Fuzzy Evaluation Subsystem

For purposes of a comparison, spatial novelty images obtained as variations between the left/right captured images in Fig.3 and between the left/right enhanced contrast ones in Fig.4 have been evaluated with the aim of a subsequent computation of their mean absolute contrast values X_μ and X'_μ. respectively. In Fig.5 both the above mentioned spatial novelty images have been reported. The mean absolute contrast value X_μ=0.1577 for the spatial novelty image $|\mathbf{\Delta G}|$ and X'_μ=0.3057 for the spatial novelty image $|\mathbf{\Delta F}|$. It can be noticed that the value X'_μ is almost twice the value X_μ. This means that enhanced contrast images obtained with the Fuzzy Evaluation Subsystem in the proposed CNN-based architecture reveal quite effective for the subsequent determination of spatial novelty images for mobile robots.

In Fig. 6 the 255-complemented image of the spatial novelty image shown in Fig. 5(b) and the corresponding histogram are shown. As it can be noticed, the features of this histogram could be significant for further processing in the stereo vision system.

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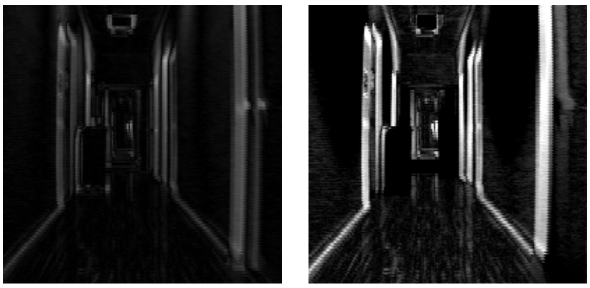
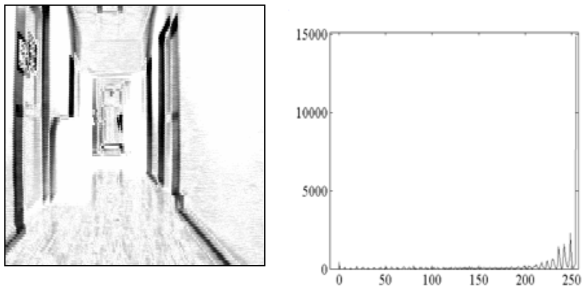


(a) (b)

Fig. 5 Absolute difference $|\mathbf{\Delta F}|$ of (a) input images and (b) output enhanced images



(a) (b)

Fig. 6 (a) 255-complemented image of $|\mathbf{\Delta F}|$ and (b) its histogram

6 Conclusions

In this paper a contribution to spatial novelty detection via image contrast enhancement in stereo-vision systems for mobile vehicles has been proposed by suggesting a CNN-based architecture properly designed to process perspective images with light-dependent semantic content. After describing the proposed architecture, image quality contrast evaluations have been performed on the obtained spatial novelty images. A test case has been reported, to show how the suggested cellular system can provide useful information for stereo vision systems.

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