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Adaptive image sensing and enhancement using the Adaptive Cellular Neural Network Universal Machine

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ABSTRACT: *A simple but powerful active image equalization method is introduced via adaptive CNN-UM sensor-computers. The method can be used for the adaptive control of image sensing and for subsequent image enhancement. The algorithm uses intensity and contrast content as well. The method is completely executable on the Adaptive Cellular Neural Network Universal Machine (ACNN-UM) architecture* [3]. *The adaptive extended cell is presented.*

1. Introduction

Due to improper or uneven lighting conditions important information may be lost during sensing. Adaptive sensing, in our case the adaptive control of exposure time can solve this problem. Exposure time computation is based on the information available during the exposure, this technique may reduce information loss. Integrated sensor-computers provide for a new and unique capacity as they dynamically control the sensors, based on interactive computation.

Another problem is that the acquired image may be improper for human visual perception. A kind of visualization can solve this problem, which means adaptive image enhancement in our case. There are several methods like amplitude scaling, contrast modification and various kinds of histogram modifications available at this time [6].

In adaptive sensing and image enhancement computation time is significant, hence using a 2D, parallel computer, like the Cellular Neural Network Universal Machine (CNN-UM [1],[2]) may be important. It is significant to use operations that are executable on the currently available CNN-UM chip or which are likely to be available in the near future.

The difference between intelligent sensing and image enhancement is that the former must be controlled in cooperation with sensing, while the later is used after sensing. Hence image enhancement cannot restore information lost during sensing (e.g. because of saturation). The task of adaptive sensing is to acquire proper image content, while the goal of enhancement is to produce an excellent result for human perception.

The adaptive CNN-UM architecture has been introduced in [3]. Among others plasticity and variable resolution in space and time are handled in this architecture. By using this architecture, unlike in "smart sensors", stored programmable spatiotemporal computing is being performed in the sensing-computing loop, interactively.

The most common method for image enhancement is histogram equalization. CNN techniques have already been used for this task [4]. The current work addresses simpler methods such as contrast and intensity equalization rather than histogram equalization.

Histogram equalization can be adaptive or nonadaptive. Certainly there are also methods combining a global method and locality [8]. However, the adaptive methods are computationally intensive. Accordingly, an interpolating technique has been proposed in [5].

Adaptive equalization in our case means that local features are considered, thus the intensities are mapped through a spatially changing function. There is no need of interpolation if the adaptive CNN-UM is used, since parallel computation enables individual adaptation for each pixel.

The novelty of our method is as follows: Contrast content is used for adaptivity, no nonlinear templates are involved and contrast equalization is included in the enhancement.

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2. Additive image enhancement based on contrast and intensity

Let I(x,y) represent a grayscale image, according to the CNN convention, on the range [-1,1] (black=1, white=-1). The image is assumed to be sampled in space, i.e. I is a matrix $I \in [-1,1]^{M \times N}$, where MxN is the size of the image.

Our goal is to find relatively simple techniques. First, the square intensity and contrast are computed and denoted as $I^2(x,y)$ and $C^2(x,y)$. Second, diffusion D is used to smooth these values in a given range. Third, a compensation mask is computed as a monotone-decreasing function of the diffused contrast and intensity, respectively. This function was chosen to be: $f(x)=c_1(1-c_2x)^n$, where c_1, c_2 and n are constants. Note that c_2 is adjusted so that f is monotone-decreasing on the interval of the actual intensity and contrast values, respectively. Compensation is computed as the multiplication of the mask and intensity or contrast. The intensity and contrast compensation are added to the original image. The resulting equation of the adaptive contrast and intensity enhancement transformation (ACIE) is as follows:

$$I(x,y) := I(x,y) + k_1 I(x,y)(1-k_2 D(I^2(x,y))^n + k_3 C(x,y)(1-k_4 D(C^2(x,y)))^m =$$
$$I(x,y) + k_1 I(x,y) M_i(x,y) + k_3 C(x,y) M_c(x,y) \quad (1)$$

where k_1, k_2, k_3, k_4, n and m are parameters. The parameters k_1 and k_3 control the magnitude of the intensity and contrast correction, respectively; k_2 and k_4 control the selectivity of the correction; n and m control the character of the compensation functions. The second term in the equation is the intensity enhancement, and the third term is a contrast enhancement. Equalizations are achieved through intensity and contrast maps (M_i, M_c). The method resembles the retinal model in [9] (see also [10] and [11]). Note that the goal of this work was not to construct a neuromorphic model but to develop a simple CNN realizable model. The ACIE method resembles the Wallis statistical differencing (see. [6] pp. 309.) as well.

The range of the diffusion, i.e. the template coefficients or execution time of the diffusion template, controls the range considered in adaptation. This execution time is denoted as T. The next two templates are used for contrast measurement (CONTRAST) and for diffusion (DIFFUS), respectively. For a detailed analysis of applicable templates see [12].

A =

0	0	0
0	1	0
0	0	0

B =

-0.6	-0.6	-0.6
-0.6	0.48	-0.6
-0.6	-0.6	-0.6

z = 0

The CONTRAST template

A =

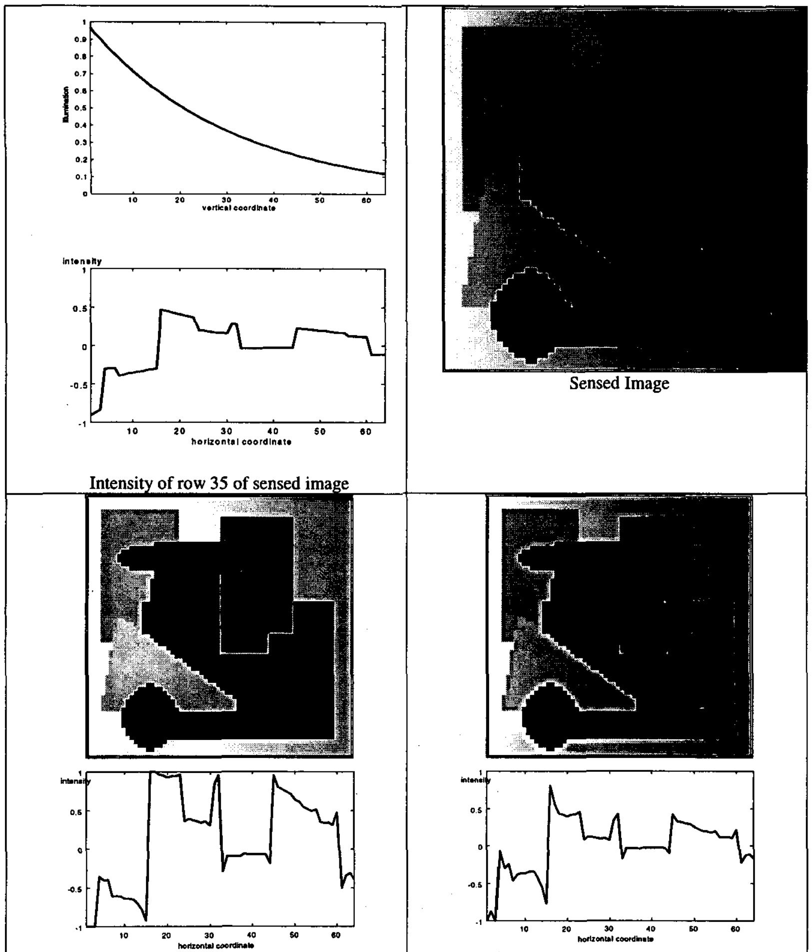
0.1	0.15	0.1
0.15	0	0.15
0.1	0.15	0.1

B =

0	0	0
0	0	0
0	0	0

z = 0

The DIFFUS template



Intensity of row 35 of sensed image

Sensed Image

Enhanced image and intensity plot in row 35

Conventional contrast enhancement and intensity plot in row 35

Figure 1 An exponentially decreasing illumination into the right direction is supposed during sensing. Note that the sensed image seems better than it is in reality, because during perception, the adaptive mechanism of the eye of the reader enhances it already, and this process is similar to the technique presented here. The ACIE restores the original image in good quality. The contrast and intensity of the image are fairly equalized. The conventional contrast enhancement technique oversaturates the contrast at some places (see the border of the black circle at the bottom left corner) while it does not improve the contrast at other places, moreover, intensity is not equalized (compare the intensity plots). The parameters of ACIE are: $k_1=1$, $k_2=2$, $k_3=100$, $k_4=5$, $T=50\tau_{CNN}$ and $n=m=3$. The equation of the conventional contrast enhancement was $I'(x,y)=I(x,y)+3C(x,y)$.

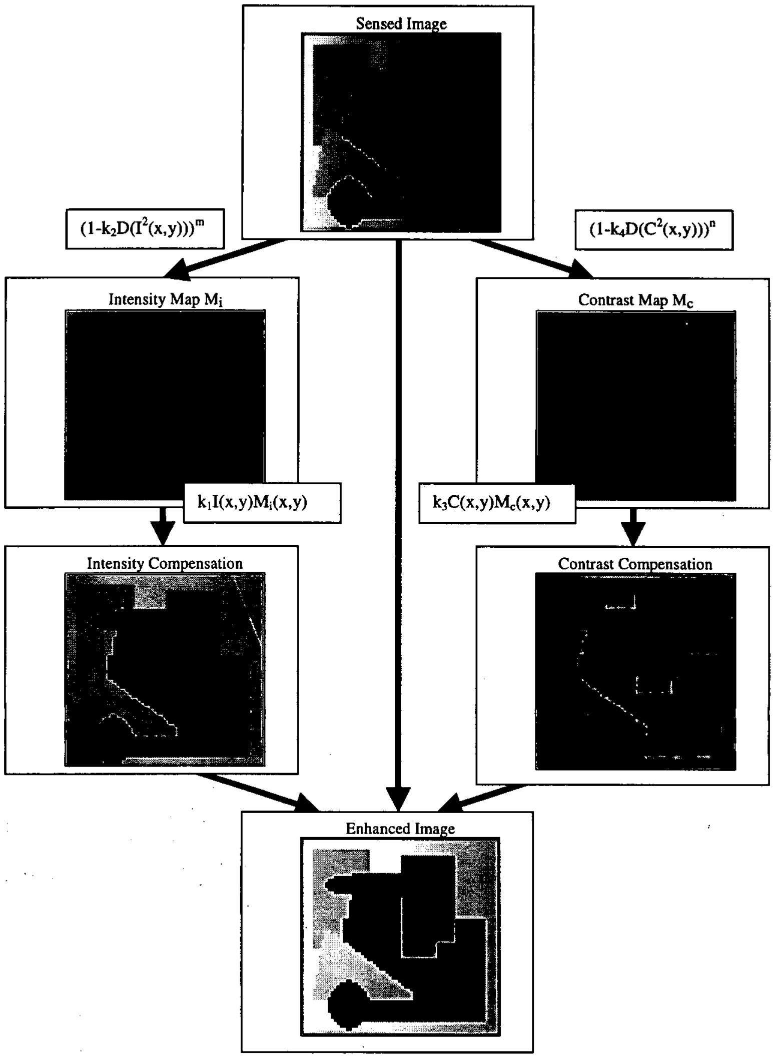


Figure 2 Outline of flowchart of the ACIE image enhancement algorithm.

3. Adaptive sensing via locally adaptive exposure time

Using uniform exposure time, the sensed image may be uneven due to changing illumination. Adaptive sensing assumes an imaging device with pixelwise programmable exposure time or gain. Adaptive sensing in our case means that the mask of the exposure time M_e is programmed adaptively during sensing. This can be achieved by a procedure described as follows. First, a short enough exposure is taken with uniform exposure, this image is denoted by I_0 Second, an exposure mask is calculated as:

$$M_e(x,y) := k_1 I_0(x,y)((1-k_2D(I_0{}^2(x,y)))^n + (1-k_3D(C^2(x,y)))^m =$$
$$k_1 I_0(x,y)(M_i(x,y)+M_c(x,y))$$

where k_1, k_2, k_3, n and m are parameters with similar meaning as before. During sensing the intensity and contrast maps are used together as an exposure map. Sensing is modeled with a multiplication with the exposure mask and threshold is also applied:

$$I_s(x,y)=Tr(I_0+I_0(x,y)M_e(x,y))$$

where I_s is the sensed image and the threshold function is $Tr(x)=\max\{-1,\min(1,x)\}$. The exposure mask is computed similarly to the compensation masks in the enhancement method. The result is not as excellent as the output of the adaptive equalization (see Figure 3), since during sensing there is no opportunity for contrast equalization. This method resembles the one used in [7] for estimating light illumination energy for color identification.

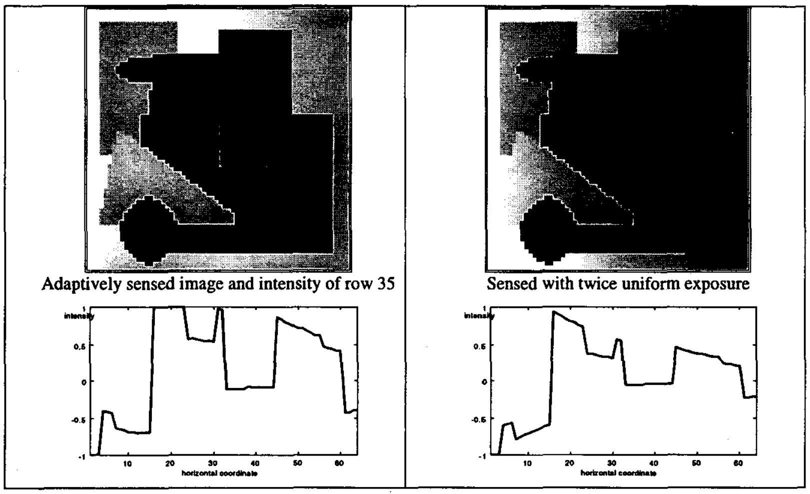


Figure 3 Adaptive image sensing equalizes intensity, it is obvious that using uniform exposure the right side will be dim: exponential decreasing tendency in absolute intensity is apparent. The parameters are the same as before for the contrast and intensity maps: $k_1=1.5$, $k_2=2$, $k_3=100$, $k_4=5$, $T=50\tau_{CNN}$, and n=m=3. Note that in reality the left picture is much worse, than it seems to be, because there is an enhancement mechanism in the human visuals system as well.

4. Realization via Adaptive Extended Cell in CNN-UM

The method introduced can easily be realized using the Adaptive Extended Cell in CNN-UM ([3]). Time invariant local control is used via local template memories TCM. The TCM memories are local analog memories associated with the cells, i.e. individual pixels. They are used to control template values. Image enhancement can be implemented by the following template:

$$A=\begin{bmatrix}0&0&0\\0&1&0\\0&0&0\end{bmatrix}\qquad B=\begin{bmatrix}c&c&c\\c&b&c\\c&c&c\end{bmatrix}\qquad z=\boxed{0}$$

where c and b are TCM values and they are computed as: $c=-0.6M_c(x,y)$ and $b=M_i(x,y)+1.48M_i(x,y)$. The masks are computed as in equation (1) and the acquired image is used as input. Adaptive sensing may be realized by enabling the TCMs to program the exposure time individually for each pixel. This work does not address the possibilities of variable resolution and real time local adaptation, but it is obvious that using our method with real time local adaptation results in a more powerful method.

5. Conclusions

An adaptive image enhancement and image sensing technique were presented. Both methods use basically the same technique for equalization as they apply the intensity and contrast information of the basic image. The equalization masks are computed by using the diffusion template via the CNN-UM. The algorithm is ideal for the ACNN-UM The most time consuming task is the diffusion. Accordingly, the use of the currently available CNN-UM chip speeds up the process significantly. On the other hand, the presented methods are of acceptable quality as this is shown by the sample images. In the algorithms the radius of the adaptation can be controlled by the time or gain of diffusion, thus all intermediate cases between full global and local equalization are dynamically available.

6. Acknowledgement

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