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Image enhancement algorithm based on improved lateral inhibition network

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HIGHLIGHTS

- A novel enhancement method based on lateral inhibition network is proposed.
- The image pixels distributed into the four pairs of sub-regions are utilized to construct the compensation measure factor.
- Introducing the compensation measure factor and median filtering is employed to optimize the proposed model.

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ABSTRACT

There is often substantial noise and blurred details in the images captured by cameras. To solve this problem, we propose a novel image enhancement algorithm combined with an improved lateral inhibition network. Firstly, we built a mathematical model of a lateral inhibition network in conjunction with biological visual perception; this model helped to realize enhanced contrast and improved edge definition in images. Secondly, we proposed that the adaptive lateral inhibition coefficient adhere to an exponential distribution thus making the model more flexible and more universal. Finally, we added median filtering and a compensation measure factor to build the framework with high pass filtering functionality thus eliminating image noise and improving edge contrast, addressing problems with blurred image edges. Our experimental results show that our algorithm is able to eliminate noise and the blurring phenomena, and enhance the details of visible and infrared images.

1. Introduction

Image enhancement is an indispensable technique and essential method of improving image quality in digital image processing. Even with the ubiquity of digital cameras and mobile telephones, there are substantial amounts of noise in images because of camera defocusing, a lack of uniform illumination, atmospheric disturbances, and the like not clear edge texture and producing dark or highlight area, i.e., which have a great impact on executing missions. Hence, it is necessary and useful to develop an effective enhancement algorithm that addresses such noise in digital images.

To remove noise from images, many denoising methods based on the features of the images, the characteristics of the noise, and spectrum distribution are proposed by scholars. They can be broadly divided into three categories: denoising methods in area space, such as mean filtering, median filtering, i.e.; denoising methods in frequency space, such as homomorphic filtering, i.e.; as well as the donising methods based on sparse representation, such as the block-match and 3D filtering, BM3D, i.e. [1–6]. Using the classical methods of image denoising, the noise was effectively removed, but the image edge easily appeared fuzzy phenomenon. In recent years, scholars worldwide have developed a variety of image enhancement algorithms from the perspective of image characteristics and various mathematical theories [7,8]; however, the actual visual effect is not necessarily favorable without also considering the visual features. To handle image information, scholars have referenced the principles of visual lateral inhibition as early as 1980 [9].

In this early research, background information of images was extracted from high levels of background interference. In subsequent research, scholars have achieved image edge detection, edge-sharpening, and enhanced contrast via the theory of lateral inhibition [10–12]. With the further development of research, scholars proposed numerous enhancement algorithms based on

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various parameters of the lateral inhibition network and the characteristics of image quality [13–17]. Some scholars proposed enhancement algorithms that combined a lateral inhibition network with adaptive filtering. Using such an approach, the system adaptively selects model parameters according to different local variances and averages of images, thus eliminating noise.

Based on the above, we proposed a new improved algorithm that incorporates a lateral inhibition network, which is equivalent to a high pass filter and sensitive to noise. Furthermore, we introduce a compensation measure factor that causes the network to enhance the edges and remove noise, thus solving the problem of image edge fuzziness. Our experimental results show that our proposed method effectively removes the noise from images and improves the quality of images.

The rest of this letter is organized as follows. Section 2 overviews the lateral inhibition network theory. Then we present the details of the proposed method to enhance images in Section 3. The experimental results are given in Section 4. Finally, a conclusion is drawn in Section 5.

2. Lateral inhibition network theory

Lateral inhibition was discovered and confirmed by the Limulus visual physiological electrical experiments [16]. Here, every Limulus eye is considered as a single receptor. When the center receptor receives a slice of strong light stimulus, the excitability of its surrounding receptors will be inhibited, and vice versa. That is called the lateral inhibition phenomenon in that the Limulus eyes produce conditionality in each other. Suppose the two receptors A, B do the experiments, assuming that the A and B are respectively lighted, whose light emitting powers are g_A and g_B, respectively; when the A and B are simultaneously lighted, detecting their light emitting powers are reduced to f_A and f_B, respectively; meanwhile, the stronger endured the degree of light stimulus by A, the smaller emitted the pulse frequency by B. That shows the receptor A is inhibited by the receptor B; on the other hand, the receptor B is also inhibited by the receptor A, called the lateral inhibition. The lateral inhibition effect can be described as:

$$\begin{aligned} g_A &= f_B - k_{BA}(f_B - f_{AB}) \\ g_B &= f_B - k_{AB}(f_A - f_{BA}) \end{aligned} \tag{1}$$

where g_A and g_B represent light emitting powers of the two receptors by single light, respectively; f_A and f_B represent light emitting powers of the two receptors with the lateral inhibition effect, respectively; k_{AB} and k_{BA} represent the lateral inhibition coefficients between two receptors; f_{AB} and f_{BA} represent the threshold value of the lateral inhibition.

Hence, we can find that the neighboring receptors' light emitting power below the threshold value doesn't produce lateral inhibition effect; besides the lateral inhibition coefficient's value depends on the distance between two receptors. In the lateral inhibition network composed of n receptors, the pth receptor is endured inhibition effect from surrounding receptors, at this moment the Eq. (1) is extended:

$$g_p = f_p - \sum_{j=1}^{n} k_{jp}(f_j - f_{pj}) \quad p = 1, 2, \ldots, n;\ j = 1, 2, \ldots, n; p \neq j \tag{2}$$

According to this principle, the receptors in the bright and dark border are inhibited, then producing noticeable bright and dark lines over there. Hence, this lateral inhibition phenomenon helps to enhance information extraction of the retina, increase both contour and contrast, and make targets much clearer and easier to recognize.

3. Image enhancement model based on lateral inhibition networks

3.1. Enhancement model

In order to make one-dimensional lateral inhibition network applied to image processing, it must be extended to that of two-dimensions. The traditional lateral inhibition algorithm adopted a non-recurrent lateral inhibition network model with ignoring the threshold value [18], which can be expressed as

$$G(m,n) = F(m,n) - \sum_{i=-l}^{l}\sum_{j=-l}^{l} k(i,j) \cdot F(m+i, n+j), \tag{3}$$

where $F(m,n)$ represents the input image, $G(m,n)$ represents the output image, $k(i,j)$ represents the inhibition coefficients matrix, and l is the inhibition field.

The traditional lateral inhibition network is sensitive to noise. The method used in [18] adopts a lateral inhibition network combined with a mean filtering to remove noise, which disperses the grayscale values of noise among the surroundings to realize smoothness; however, images often become fuzzy as a result. Compared with mean filtering, median filtering results in a better smoothness and clearer contour. Therefore, we process images with a lateral inhibition network combined with median filtering to remove noise, which is expressed as:

$$G(m,n) = \overline{F(m,n)} - \sum_{i=-l}^{l}\sum_{j=-l}^{l} k(i,j) \cdot F(m+i, n+j), \tag{4}$$

$$\overline{F(m,n)} = \underset{(r,s)\in(-l',l')}{median}[F(k_1 + r, k_2 + s)]. \tag{5}$$

where $F(m,n)$ represents $F(m,n)$'s median value in its neighborhood and l' is the size of the median filtering window.

To remove noise and avoid edge fuzziness, we introduce a compensation measure factor to suppress noise signal. When it is greater than a given threshold value, considered as a valid signal mutation and carried on enhancing this signal; and vice, considered as a noise mutation and carried on inhibiting noise. For one-dimensional signal with noise, if there is signal intensity mutation near the mutational site, the signal intensity has some correlation each other; if there is signal intensity mutation near the noise point, the signal intensity has no correlation each other. The signal average intensity is not equal located in the mutational site on both sides, but the signal average intensity is very approximate located in the noise point on both sides. For the images, the edge points are grayscale mutational sites with a certain direction, and define a direction perpendicular to the grayscale mutational site as edge direction. Hence, most can be found at least one edge point along the edge directions in any neighborhood of the edge points. Using the edge points along the edge direction, the neighborhood pixels can be divided into at least two sub-regions, whose internal grayscales are homogeneous distribution. However, the difference of grayscale is larger between the two sub-regions; but there is not this feature for the noise in the smooth region.

The compensation measure factor processes pixels by distributing into the four pairs of sub-regions shown in Fig. 1. The neighborhood of every pixel in the image is divided into two equal parts, each of which is processed using median filtering and a 5×5 template. On each subsidiary neighborhood, the number of pixel (m,n) is respectively t_1 and t_2, with grayscale values of pixels is p_{1i} and