EDGE DETECTION BASED ON DECISION-LEVEL INFORMATION FUSION AND ITS APPLICATION IN HYBRID IMAGE FILTERING

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ABSTRACT

A new edge detection method based on decision-level information fusion is proposed to classify image pixels into edge and non-edge categories. Traditional edge detection algorithms make detection decision under a single criterion, which may perform inefficiently with the change of noise model. We use fusion entropy as a criterion to integrate decisions from different classifiers in order to improve the edge detection accuracy. The proposed decision fusion based edge detection method is applied to image filtering and leads to a weighted hybrid-filtering algorithm. Simulation results show that the new edge detection method has better performance than the single criterion edge detection methods.

1. INTRODUCTION

Linear and nonlinear filtering techniques are widely used in image processing to remove noises introduced in the acquisition or transmission of digital images. Linear filtering is good at smoothing additive Gaussian noise, while nonlinear filtering is more effective in removing impulsive noise. However, both of them have inherit limits. For example, linear filtering can blur signal border, and nonlinear filtering is poor at dealing with uniformly distributed noises. Hybrid linear and nonlinear filtering technique [1, 2] can combine the advantages of the two filtering techniques and avoid their weaknesses. Hybrid filter usually chooses the proper filter according to pixel classification result, i.e., whether the pixel is an edge point or non-edge point. Traditional edge detection methods make detection decision based on single criterion. When the image boundary is blurred or the noise model is complicated, the performance of single criterion edge detection methods turns to be inefficient, which may affect the image filtering performance as well.

To reduce the uncertainty of single-source decision, we propose to integrate multiple decisions obtained under different pixel classification criterions. Decision-level information fusion is a very important part in an intelligent system. It can eliminate redundancy and resolve conflicts between multiple information sources. Generally speaking, the fusion scheme is designed to weigh the strength of individual decision according to the probabilistic model, so as to retain and enhance the right or useful information of multiple criteria. Therefore the classifier based on information fusion usually has better performance than the single criterion classifier.

In this paper, a novel concept of fusion entropy is developed for the design of decision combination rule. The experimental results demonstrate that the proposed detection method is more accurate than the traditional single criterion edge detection methods, and can improve the image filtering performance.

2. EDGE DETECTION BASED ON SINGLE CRITERION

We briefly describe the traditional edge detection methods. Let (m, n) be the index of an image pixel. The pixel intensity can be represented as

$$f(m, n) = b(m, n) + v'(m, n) \tag{1}$$

where $b(m, n)$ is the true value of the pixel intensity and $v'(m, n)$ is the random noise in the 2-D image. Without loss of generality, we assume that there are two possible image patterns in the neighborhood region of (m, n). One is the homogeneous pattern, where the gray values of all pixels are close to each other. Another is the boundary pattern, where there exist two or more sections with quite different mean intensities. To detect the abrupt change of image intensities within the local filter window, we can form two square filter windows that lie at the opposite side of the current pixel (m, n). Let the size of the two windows be $M \times M$. The mean intensities of the two windows can be computed, and denoted by m_L and m_R respectively. Let $T(m, n) = m_L - m_R$ be the intensity difference of the two filter windows. The traditional edge detection methods compare $T(m, n)$ with a threshold to determine whether the pixel (m, n) is a boundary point. The threshold value usually varies with different detection criterion.

In this paper, we adopt two commonly used criterions to explore the potential of decision-level information fusion. One is the minimum total error probability criterion (MTEPC). Another is the Neyman-Pearson criterion (N-PC). Based on the MTEPC, we can get the following equivalent test

$$T(m,n) \underset{H_0}{\overset{H_1}{\gtrless}} \frac{\sigma_1^2}{(M \times M)h} \ln \eta + \frac{h}{2} \tag{2}$$

where H_0 and H_1 represent non-boundary point and boundary point respectively, h is the mean intensity difference between two homogeneous regions, and η is the ratio of the probability of the pixel lying in the boundary region over the probability of the pixel lying in a homogeneous region. With the Neyman-Pearson criterion, we want to minimize the miss probability P_m under the condition of constant false alarm probability P_f. Hence we can form the Lagrange function $J_\lambda = \lambda P_f + P_m$. Minimizing this function leads to the following equivalent test

$$T(m,n) \underset{H_0}{\overset{H_1}{\gtrless}} \frac{\sigma_1^2}{(M \times M)h} \ln \lambda + \frac{h}{2}. \tag{3}$$

Both of the above two detection tests make classification decision under single criterion. Generally speaking, an optimal decision under one criterion may not be optimal under another criterion.

3. THE FUSION ENTROPY CRITERION

To improve the accuracy of edge detection, we propose to integrate decisions from individual classifiers to make the final edge detection decision. Decision-level information fusion is an important technique that can remove redundant information and resolve conflicts between multiple information sources. The fusion scheme, or combination rule, is critical in a fusion system. There are a variety of information fusion schemes one can use for the edge detection. They include the classical statistical decision theory [3], Bayesian reasoning, Dempster-Shafer theory of evidence [4] and the fuzzy set theory [5]. In this paper, we use a modified version of fusion entropy and perform decision-level fusion of the two criteria introduced in Section 2 to obtain the final edge detection decision. As the first step of study, we only adopt two criterions. In fact, the more criterions used in a fusion system, the better the detection performance.

Let MTEPC be the information sub-source E_1 and N-PC be the information sub-source E_2. The decisions of E_1 and E_2 are the inputs to the fusion system. The sub-source decision has two target classes, i.e., S_1 is non-boundary point and S_2 is boundary point.

Definition 1 *Let $\vec{m}_i = (m_{i1}, m_{i2})$ be the decision of sub-source E_i, $i = 1, 2$, where m_{ij} is the confidence degree of the jth target class in the decision of the sub-source E_i, $0 \le m_{ij} \le 1$ and $\sum_{j=1}^{2} m_{ij} = 1$.*

The decision $\vec{m}_i$ can be computed from equation (2) and equation (3) respectively. The larger the m_{ij} is, the more likely the pixel belongs to the jth target class in the decision of the sub-source E_i.

3.1. Description of Information Uncertainty and Consistency

To derive the fusion criterion, we define the confidence degree $1 - P_{ei}$, the uncertainty Q_i and consistency degree C_i of a sub-source decision, as functions of $\vec{m}_i$ and its error probability P_{ei}. In a sub-source decision $\vec{m}_i$, the entry m_{ij} can be regarded as the membership degree of a fuzzy set. So we have the following definition of uncertainty.

Definition 2 *The uncertainty Q_i of the sub-source decision $\vec{m}_i$ is the fuzzy entropy weighted by the confidence degree of the decision, i.e.,*

$$Q_i = -(1 - P_{ei}) \sum_{j=1}^{2} \left(m_{ij} \log(m_{ij}) + (1 - m_{ij}) \log(1 - m_{ij}) \right), \tag{4}$$

where P_{ei} is the error probability of $\vec{m}_i$ obtained through experiments, $(1 - P_{ei})$ is the confidence degree of $\vec{m}_i$.

It can be seen from the definition that Q_i increases with the uncertainty of the decision $\vec{m}_i$.

Although Q_i can be used to measure the uncertainty of a single sub-source decision, it cannot be employed to measure the consistency between multiple sub-source decisions, because the function is uncorrelated with the other sub-source decisions. To design the metric of consistency, we need the definition of the distance between two sub-source decisions.

Definition 3 *The Euclidian distance between two sub-source decisions $\vec{m}_i$ and $\vec{m}_k$ is*

$$d_{ik} = \sqrt{\sum_{j=1}^{2} (m_{ij} - m_{kj})^2}, \quad i = 1, 2; k = 1, 2. \tag{5}$$

Definition 4 *The consistency between the sub-source decision $\vec{m}_i$ and any other sub-source decision is*

$$C_i = \frac{e^{D_i}}{\sum_{k=1}^{2} e^{D_k}}, \tag{6}$$

where $D_i = \sum_{k=1}^{2} d_{ik}$, and $0 < C_i \le 1$.

Based on the definition, C_i describes the difference of each target classes within the sub-source decision. So it reflects the consistency of sub-source decision $\vec{m}_i$ with respect to the other sub-source decisions. The consistency decreases as the value of C_i increases.

We now can introduce the concept of fusion entropy based on the definitions of the confidence degree $(1 - P_{ei})$, the uncertainty Q_i and the consistency C_i of a sub-source decision.

Definition 5 *The fusion entropy of the sub-source E_i is the multiplication of its decision consistency and uncertainty*

$$H_i = C_i \cdot Q_i. \tag{7}$$

The fusion entropy is proportional to the uncertainty, and inversely proportional to the sub-source performance and consistency. So the smaller the fusion entropy is, the more reliable the decision is. It integrates the characters of the three measures introduced above, and is more comprehensive than any one of them. Hence, it can better describe the essence of the observation space. We use it to derive the weighting coefficients in the fusion system to efficiently exploit the information from multiple sub-sources.

3.2. The Fusion Criterion and Edge-preserving Image Filtering

During the fusion process, the relative weight of each target class is continuously modified via the equation

$$m'_{ij} = \sum_{k=1}^{2} \phi_{ik} \cdot m_{kj} \quad i = 1,2; k = 1,2; j = 1,2 \tag{8}$$

where ϕ_{ik} is the modification coefficient of each target class, and $\sum_{k=1}^{2} \phi_{ik} = 1$, until such a process goes to the static state that the next modification no longer changes the previous result. So ϕ is a 2×2 random matrix, and can be regarded as the one-step transition matrix of a first order Markov chain. According to the limit theory of Markov chain, such a matrix converges to a normal distribution, and the distribution vector is a row vector $Z = (z_1, z_2)$ and $\sum_{i=1}^{2} z_i = 1$, which satisfies $Z\phi = Z$. For the jth target class, Z can be used as the weighting coefficients. The fusion result can then be expressed as

$$m(j) = \sum_{i=1}^{2} z_i \cdot m_{ij} \quad i = 1,2; j = 1,2. \tag{9}$$

The proper value of Z can be obtained by minimizing the mean square error of the total fusion entropy. Let $g = \sum_{i=1}^{2} \alpha_i \cdot H_i$ be a linear combination of individual fusion entropy, where $\alpha = (\alpha_1, \alpha_2)$ is the weighting coefficient vector. The mean square error of g is

$$E([g - \bar{g}]^2) = \sum_{i=1}^{2} \alpha_i^2 \cdot \sigma_i^2 \tag{10}$$

where $\sigma_i^2 = E([H_i - \bar{H}_i]^2)$, i=1,2. Using Lagrange method to minimize equation (10) with the constraint $\sum_{i=1}^{2} \alpha_i = 1$, we can obtain the optimal solution $\alpha_1 = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$ and $\alpha_2 = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}$.

Therefore, the proper value of Z is given by $z_i = \alpha_i$. The final fusion result is

$$i = \arg\max_j \sum_{i=1}^{2} \alpha_i \cdot m_{ij} \quad j = 1,2 \tag{11}$$

where $i = 1$ means the pixel is not a boundary point, and $i = 2$ means the pixel is a boundary point.

In the design of the hybrid linear and nonlinear filter, we adopt median filter as the nonlinear filter to preserve the edge information. The hybrid filter based on the fusion of MTEPC and N-PC for boundary detection can be expressed as

$$\hat{b}(m,n) = \begin{cases} [m_L \quad m_R][w_1 \quad w_2]^T & i = 1, \\ \text{median}\{m_L, f(m,n), m_R\} & i = 2, \end{cases} \tag{12}$$

where m_L and m_R are the mean intensities in the two sub-windows, and w_1, w_2 are the weighting coefficients.

4. EXPERIMENTS AND RESULTS

To demonstrate the effectiveness of the fusion based edge detection method, we compare it with the edge detection methods that are based on single criterion, i.e. MTEPC and N-PC, separately. Each edge detection method leads to a different hybrid filter, since the hybrid filter is design to switch between median filter and linear filter according to the edge detection result. We apply the resulted three hybrid filters to two noise-contaminated images. The size of both images is 512×512. The experimental results of the three algorithms are shown in Fig. 1 and Fig. 2.

In Fig. 1 and Fig. 2, we can find that the former two algorithms suppress the noise to some extent, but the edges in the images are seriously blurred. The fusion based algorithm proposed in this paper can not only suppress the noise, but also retain the edge information very well. Thus the target and background in subfigure (d), which is the outcome of the new hybrid filtering algorithm, are clearer than that of subfigure (b) and (c) in both Fig. 1 and Fig. 2.

In Table 1, we numerically compare the performances of the three algorithms as applied to the two images. Three statistic quantities are used to measure the performance, which are the normalized mean squared error (NMSE), the peak mean squared error (PMSE) and signal-noise ratio (PSNR).

It can be seen in Table 1 that the performances of MTEPC and N-PC algorithm are comparable, while both of them are inferior to the fusion based algorithm. The performance difference is relatively large.

Table 1. Performance comparison of three algorithms.

	Detection Method	NMSE	PMSE	PSNR
Fig. 1	MTEPC	0.0079	0.0028	25.56
	N-PC	0.0083	0.0029	25.43
	Fusion based	0.0045	0.0013	27.48
Fig. 2	MTEPC	0.0098	0.0031	24.42
	N-PC	0.0083	0.0029	25.61
	Fusion based	0.0056	0.0016	26.95

Based on the above experimental results, we can conclude that the fusion based edge detection method is more accurate than the single criterion edge detection method and results a more efficient hybrid image filter.

(a) Original noisy image

(b) MTEPC

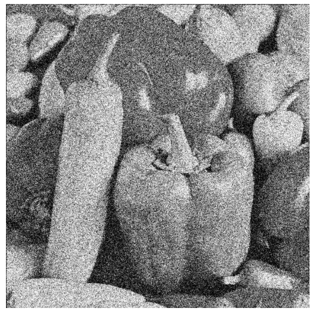
(c) N-PC

(d) Fusion based

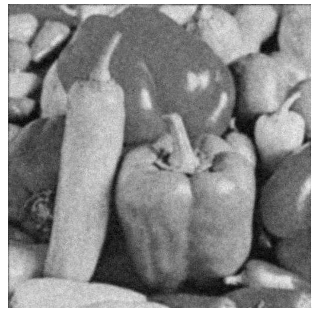
Fig. 1. Experimental results of the image Lenna.

5. CONCLUSIONS

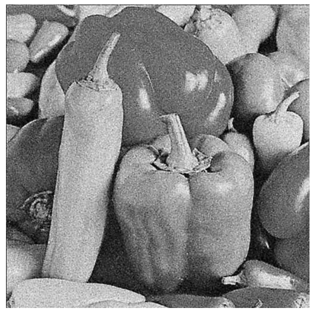
In this paper, the concept of fusion entropy is developed to design an information fusion system for edge detection. The weighting coefficients in the decision combination rule are adaptively determined based on the unbiased estimation of fusion entropy and minimum mean square error principles. This new method can remove redundant information, resolve conflicts between multiple detection decisions, so as to retain and enhance the useful information and obtain more reliable edge detection decision. The method has been compared with the traditional single criterion edge detection methods in the application of image filtering. The experimental results can demonstrate the efficiency of the proposed method. In the future research, more detection criterions can be included in the fusion system to enhance the detection performance.



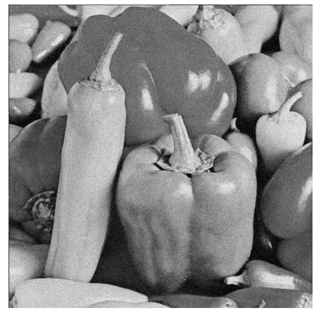
(a) Original noisy image



(b) MTEPC



(c) N-PC



(d) Fusion based

Fig. 2. Experimental results of the image peppers.

6. REFERENCES

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