TOPOLOGICAL-STABILIZATION BASED THRESHOLD QUANTIZATION FOR ROBUST CHANGE DETECTION

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ABSTRACT

A threshold quantization algorithm for robust change detection is proposed in this paper. According to the threshold distribution of difference frames, a 4-level Lloyd-Max quantizer is designed, and then, based on the topological stabilization of video frames, the Lloyd-Max quantizer is refined by a linear adjusting function to form the proposed threshold quantizer. Objective and subjective experiments show that the proposed quantizer greatly improves the robustness of the thresholding methods for change detection thus significantly improves the quality of change masks without increasing computation loads.

***Index Terms*—** Image processing, quantization, image segmentation

1. INTRODUCTION

Change detection (CD) techniques, which detect regions of change (RCG) in frames of the same scene, are widely used in video coding, remote sensing, and video surveillance. Frame differencing followed by thresholding is popular CD due to its simplicity [1]. However, gray-level distribution based thresholding methods [2, 3] are sensitive to noise and illumination changes, and spatial-property based thresholding methods [4, 5, 6] are robust but not spatial stable and computationally expensive. In this paper, we aim at enhancing the gray-level distribution based thresholding for CD while keeping their computation load low by a novel topological stabilization based threshold quantization algorithm.

Generally, objects in real-world videos have temporal coherence and the scene conditions do not change abruptly between scene changes. Therefore, the true threshold of difference frames should be temporally stable. Quantization is an effective way to suppress the temporal variations of estimated thresholds. However, few quantization methods are proposed for CD. Wang [7] directly selects a threshold from a quantized frame histogram and may fail when the histogram is unimodal. Kundu [8] performs frame thresholding by quantizing each pixel of a frame using a 2 (or multiple)-level Lloyd-Max quantizer. But it may seriously underthreshold a difference frame under challenging video conditions.

A threshold quantization algorithm for fast and robust CD is proposed in this paper. Section 2 statistically models the threshold distribution, and then describes the proposed threshold quantizer in detail. Section 3 evaluates the proposed threshold quantizer. Conclusions are presented in Section 4.

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2. THE PROPOSED ALGORITHM

The proposed algorithm is based on threshold distribution analysis and the Lloyd-Max quantization algorithm [9], which minimizes the mean square error (MSE) for a given number of quantization levels. First, the true thresholds of difference frames are approximated by a subjective evaluation procedure (Sec. 2.1). Second, the statistical model of the threshold distribution is obtained based on the estimated true thresholds (Sec. 2.2). A Lloyd-Max quantizer is then obtained based on the threshold statistical model. At last, the Lloyd-Max quantizer is refined by a linear heuristic adjusting function (Sec. 2.3). The CD algorithm in [10] is used to get difference frames $\{D_n\}$, where n is time instant.

2.1. True threshold approximation

To obtain a reliable threshold distribution of $\{D_n\}$, a vast number of true thresholds are necessary to form the threshold learning set $\{t_L\}$. However, it is impractical to obtain the true thresholds purely subjectively since it involves large tedious works. In this paper, we approximate the true thresholds by two steps: 1) obtain the thresholds as well as the binary results by a high-performance thresholding method, and 2) subjectively evaluate the binary results and remove the thresholds which lead to low-quality binary results.

Rosin *et al.* [4, 11] show that the Poisson-noise modeling thresholding is one of the best thresholding methods for CD. Therefore, we use the thresholding method to approximate the true thresholds. Totally 27 real-world videos with different contents and noise levels are used, and 9220 thresholds are obtained. After subjectively evaluating the binary results, 1177 are removed from the learning set. Note that we assume that the noise in $\{D_n\}$ is additive white Gaussian noise

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(AWGN) in this paper.

2.2. Threshold distribution analysis and modeling

The RCG in $\{D_n\}$ are caused by not only important changes (e.g., objects movement) but also unimportant changes (e.g., noise or shadows). True thresholds of $\{D_n\}$ should suppress unimportant changes without damaging important changes. Fig.1 shows an example of the threshold distribution based on the learning set $\{t_L\}$. Note that $0 \leq t_L \leq 255$. As can be seen, the thresholds in $\{t_L\}$ can be divided into 4 classes, i.e., the thresholds for very weak RCG (VWRCG), weak RCG (WRCG), strong RCG (SRCG), and very strong RCG (VSRCG), by fixing three valleys v_1, v_2 and v_3 in the threshold distribution curve. Assume that event E_1, E_2, E_3 and E_4 are “a difference frame contains VWRCG, WRCG, SRCG, and VSRCG”, respectively, where events E_1, E_2, E_3, and E_4 are mutually exclusive. We model the distribution of $\{t_L\}$ as a random variable T. Based on the *theorem on total probability*, the probability density function (pdf) $p(t)$ of T is

$$p(t) = \sum_{i=1}^{4} p(t|E_i)P[E_i], \tag{1}$$

where $i = 1, 2, 3$ and 4, $P[E_i]$ is the probability of event E_i.

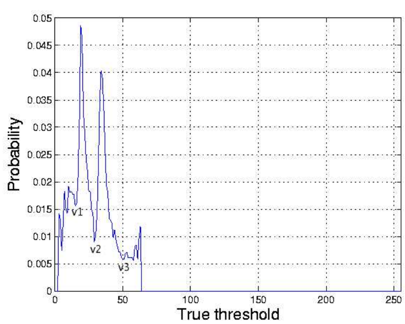


Fig. 1. True-threshold distribution of D_n.

We model each conditional pdf $p(t|E_i)$ as a Gaussian distribution with mean m_i and variance σ_i^2. Thus,

$$p(t) = \sum_{i=1}^{4} N(m_i, \sigma_i^2) \cdot P[E_i], \tag{2}$$

where

$$N(m_i, \sigma_i^2) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(t-m_i)^2}{2\sigma_i^2}}. \tag{3}$$

By using the maximum likelihood estimation, the mean and variance of a Gaussian random variable can be estimated by the population mean and population variance. Therefore, the parameters m_i and σ_i^2 in (3) can be estimated by computing the mean and variance of the thresholds belong to E_i in the learning set $\{t_L\}$. Fig.2 shows an example of the statistical model of the true threshold distribution shown in Fig.1.

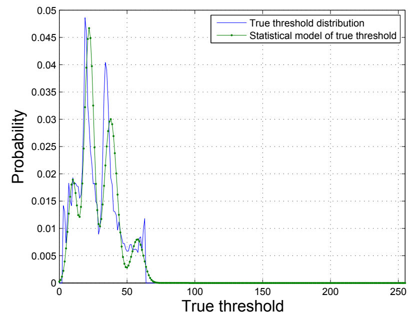


Fig. 2. Modeling the true-threshold distribution for D_n.

2.3. Threshold Quantization

The pivotal step of designing a quantizer is to find the partition levels $\{a_k\}$ and the corresponding reproduction levels $\{r_k\}$, where $k = \{1, 2, \cdots, M\}$, and M is the number of quantization levels. We design the proposed threshold quantizer with four reproduction levels corresponding to the thresholds for the classes VWRCG, WRCG, SRCG, and VSRCG. Based on Lloyd-Max algorithm [9] and the pdf of T given in (2), we can obtain the four reproduction levels $\{r_1, r_2, r_3, r_4\}$ and three partition levels $\{a_1, a_2, a_3\}$ of the Lloyd-Max threshold quantizer.

Since a Lloyd-Max quantizer quantizes any data in $(a_{k-1}, a_k]$ to be r_k, the threshold quantizer may not work well for the thresholding methods which tend to underthresholding a D_n, because it is possible that a threshold is quantized to be much more lower. This may be more serious when thresholding noisy videos or videos with serious local changes (e.g., local changes due to door opening).

It has been shown in [5, 6] that video frames have topological stabilization, i.e., the number of RCG in D_n is relatively stable over a range of thresholds. Rosin *et. al.* [5] show that counting the number of RCG can be replaced by computing the Euler number in practice. As the threshold increasing, the Euler number of D_n tends to be stable over a range of thresholds (Fig.3). Thus the change masks of a D_n generated by different thresholds remain stable over the threshold range [5]. Based on this observation, we can refine the Lloyd-Max quantizer by increasing r_k to increase its robustness to noise and local changes. For the thresholds which underthreshold D_n, the refined quantizer can significantly improve the quality of change masks. For the thresholds which does not underthreshold D_n, the refined quantizer will not seriously degrade change masks due to the stabilization of change masks in relatively large threshold ranges.

In this paper, we refine the Lloyd-Max threshold quantizer with a linear heuristic adjusting function.

$$\begin{aligned} r_k^t &= r_k + \alpha_k \cdot \sigma_k \\ a_k^t &= a_k, \end{aligned} \tag{4}$$

where, r_k^t and a_k^t are the reproduction level and partition level

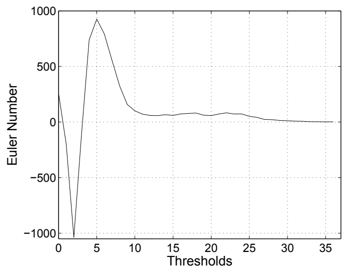


Fig. 3. Thresholds vs. Euler number.

of the proposed threshold quantizer, respectively, and α_k is a constant factor for σ_k, the standard deviation of the thresholds belonging to k-th class. To avoid overthresholding, it is not necessary that α_k always makes r_k^t be in the stable Euler number region thus α_k need not be adaptively set.

3. EVALUATION AND COMPARISON

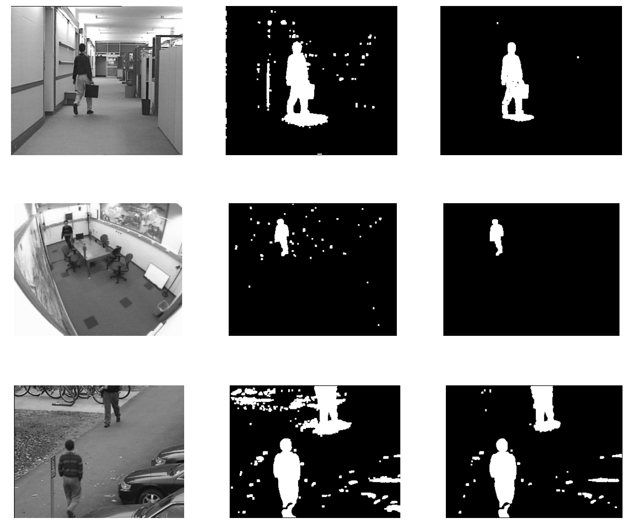
Based on the learning set $\{t_L\}$, we model $p(t|E_1)$, $p(t|E_2)$, $p(t|E_3)$ and $p(t|E_4)$ as $N(10.01, 3.39^2)$, $N(22.01, 3.43^2)$, $N(37.82, 4.65^2)$ and $N(57.67, 4.49^2)$, respectively. Based on the observation of the contents of learning video set, the prior probabilities $P[E_1]$, $P[E_2]$, $P[E_3]$, and $P[E_4]$ are selected between $0.1-0.2$, $0.25-0.4$, $0.25-0.4$, and $0.05-0.1$, respectively. In this paper, we set $P[E_1] = 0.16$, $P[E_2] = 0.40$, $P[E_3] = 0.35$, and $P[E_4] = 0.09$. Thus the pdf of T given in (2) is determined. The partition levels $\{a_k\}$ and the reproduction levels $\{r_k\}$ of the Lloyd-Max quantizer are then computed as $\{a_1, a_2, a_3\} = \{26, 37, 50\}$ and $\{r_1, r_2, r_3, r_4\} = \{19, 32, 41, 59\}$, respectively. By observing the output of the learning set, adjust factor α_1, α_2, α_3 can be selected between $1.0-1.5$, and α_4 is between $0.3-0.5$ for avoiding seriously overthresholding. We set $\{\alpha_1,\ \alpha_2,\ \alpha_3,\ \alpha_4\}$ = {1.18, 1.18, 1.08, 0.45} in (4), thus the proposed threshold quantizer is

$$\begin{array}{lcl} \{r_1^t, r_2^t, r_3^t, r_4^t\} & = & \{23, 36, 46, 61\} \\ \{a_1^t, a_2^t, a_3^t\} & = & \{26, 37, 50\}. \end{array} \tag{5}$$

The evaluation is performed by applying the proposed threshold quantizer to the output of the gray-level distribution based Kapur thresholding algorithm [2], which is found to be suitable for CD but perform worst among the thresholding methods for CD recommended in [11]. Difference frames are obtained by the CD in [10].

The videos we used for testing the proposed quantizer are disjoint from the learning video set. They are: "Hall" (300 frames of size 352×288, well illuminated, low-noise, and some local light changes), "Intelligent room" (300 frames of size 320×240, well illuminated but serious local light changes), and "Survey" (1000 frames of size 320×240, relatively high noise and serious local changes caused by light-source and shadows).

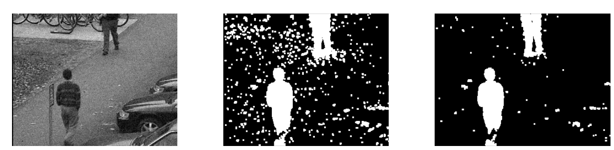
Fig.4 shows sample comparison results of "Hall", "Intelligent room", and "Survey". As can be seen, the Kapur method with the proposed threshold quantizer significantly outperforms the original Kapur method.



(a) (b) (c)

Fig. 4. Comparison between the Kapur thresholding without and with the proposed quantizer. (a) original frames of "Hall" (F_{48}), "Intel. room" (F_{215}), and "Survey" (F_{48}); (b) object masks of (a) obtained by Kapur method; (c) masks of (a) by Kapur method with the proposed quantizer.

To test the noise robustness of the proposed quantizer, 25 dB PSNR noisy "Survey" is used. Fig.5 shows that the proposed quantizer clearly improves the noise robustness of the Kapur method thus improves the quality of change masks.

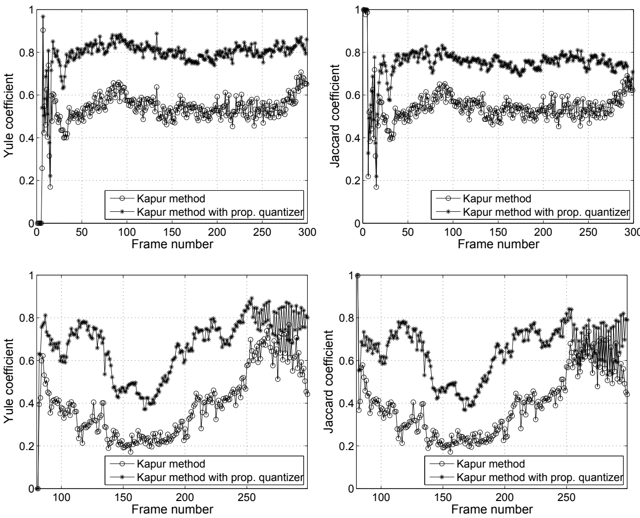


(a) (b) (c)

Fig. 5. Comparison on noisy "Survey" 25 dB. (a) F_{198}; (b) masks by Kapur method; (c) masks by Kapur method with the proposed quantizer.

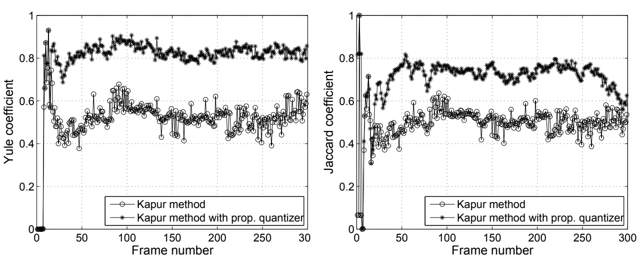
In addition, the objective measures Jaccard similarity coefficient (JC) and Yule coefficient (YC) using ground truth are used [4]. The higher a measure is, the better the thresholding is. As can be seen in Fig.6, the proposed quantizer significantly improves the performance of the Kapur method.

To objectively evaluate the noise robustness of the proposed threshold quantizer, the YC and JC measures are applied to the noisy 25 dB "Hall". As shown in Fig.7, the Kapur method with the proposed threshold quantizer clearly outperforms the original Kapur method.



(a) YC measure. (b) JC measure.

Fig. 6. Object measures comparison on “Hall” (top) and “Intel. room” (bottom).



(a) YC measure. (b) JC measure.

Fig. 7. Objective measures on “Hall” with PSNR = 25 dB.

To test the efficiency of the proposed quantizer, we integrated it into a CD method [10] that includes a frame-differencing step and a thresholding step and applied it to quantize the thresholds obtained by the thresholding step. The two-step CD method used requires on average 1.95×10^{-2} second per 352×288 frame. The proposed 4-level threshold quantizer requires 3.34×10^{-5} second per 352×288 frame. Thus the proposed quantizer adds very tiny computational time (0.17% of the time required for the CD used). Note that the frame rate of the proposed quantizer is constant and does not depend on the frame size or content. This is because the proposed quantizer only processes the thresholds obtained by the thresholding step and not the content of a video frame.

4. CONCLUSION

The threshold distribution of difference frames is modeled as a mixed Gaussian distributions of the threshold distributions for very weak, weak, strong, and very strong regions of change. A Lloyd-Max quantizer is then designed based on this statistical model. The proposed threshold quantizer is obtained by refining the Lloyd-Max quantizer with a linear adjusting function based on the topological stabilization of video frames. Both subjective and objective evaluations show that the proposed quantization algorithm clearly improves the performance of the gray-level distribution based thresholding methods without increasing computation loads.

5. REFERENCES

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