Novel texture feature persistence metric for automatic-target-recognition-directed image compression

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Abstract. We present a novel texture feature persistence metric for automatic-target-recognition (ATR)-directed image compression based on the similarity between shapes. On the basis of spatial fuzzy representation of shapes, a similarity metric between shapes is proposed. Then the impact of lossy image compression on ATR performance is measured by the similarity between shapes, which are obtained by identical segmentation and edge extraction of the source image and degraded image after compression. Experimental results show that this metric effectively measures the extent to which target texture features are preserved after compression.
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1 Introduction and Background

Digital tactical surveillance and reconnaissance systems play a vital role in the modern battlefield scenario. The images captured by the sensors located on mobile ground-based vehicles or airborne platforms (e.g., unmanned aerial vehicles) need to be transmitted on limited bandwidth tactical data links to processing stations for automatic target recognition/detection (ATR/D). Due to the limited bandwidth channels, images are compressed prior to transmission. Inevitably the lossy compression will have an impact on the ATR performance to some extent.

How to measure the impact of image compression on ATR performance is one of the central problems in ATR-directed image compression.[1] The traditional metrics are mean squared error (MSE) and peak signal-to-noise ratio (PSNR). These metrics assign a single number to the whole image, and therefore, localized evaluation of distortion on the different regions does not occur. Szu et al. introduced a computational metric called feature persistence measure (FPM), which employs a composite wavelet transform to tune the characteristic wide-band texture frequency of the target.[2,3] It counted the points of texture in the area of interest as FPM, without considering the spatial distribution information of these points. Kosheleva et al. proposed a series of segmentation-based area metrics to measure the percentages of different points between two binary images, which are the results of identical processing on the original and the codec images.[4,5]. These metrics considered only the area information of different points between two segmented binary images. In this study, we establish the texture feature persistence metric (TFPM) based on the shape similarity[6,7] from the viewpoint of typical ATR processes.

For the typical texture-based ATR applications, the images to be recognized are segmented first to find the region of interest that the targets probably lie in. Then the segmented images are edge-extracted to obtain the texture information of the targets. At last, the binary edge images are matched to the edged templates to determine which classification the target belongs to.

A block diagram of the system for evaluating the impact of image compression on ATR performance is shown in Fig. 1. The source image I_{source} and images after compression $I_{\text{codec-}i}$ $(i=1,2,\ldots,N)$ are segmented and edge-extracted to be shapes with target texture information denoted by S_{source} and $S_{\text{codec-}i}$ $(i=1,2,\ldots,N)$. The similarity metric between S_{source} and $S_{\text{codec-}i}$, denoted by SM_i, represents the impact of the i'th compression scheme on texture features in the original image. If $SM_i < SM_j$, it means that $S_{\text{codec-}j}$ matches S_{source} more closely than $S_{\text{codec-}i}$. Then we could say that the j'th compression scheme preserves more texture features and has less impact on ATR performance than the i'th compression scheme.

2 Shape Similarity and Feature Persistence Metric

2.1 *Point Fuzzy Subset*

A shape S can be treated as a set of points in the 2-D plane, $S=\{p_i \mid p_i=(x_i,y_i), i=1,2,\ldots,N\}$. If the point p_i is fuzzed to a point fuzzy subset $\tilde{p}_i$ in the 2-D plane with membership function $f_{\tilde{p}_i}(x,y)$, the point set of shape S can be transformed to fuzzy subset $\tilde{S}$. For a point (x,y) in the 2-D plane, its membership in fuzzy set $\tilde{S}$ is

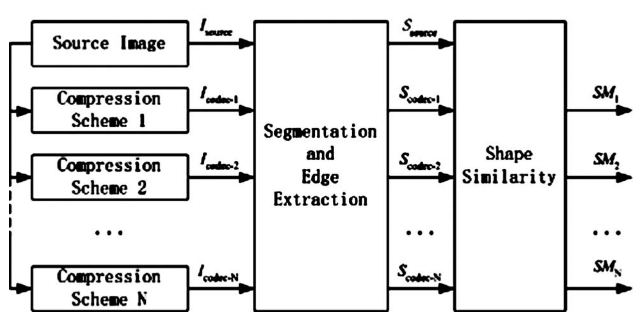

Fig. 1 Diagram of ATR-directed image compression quality evaluation system.

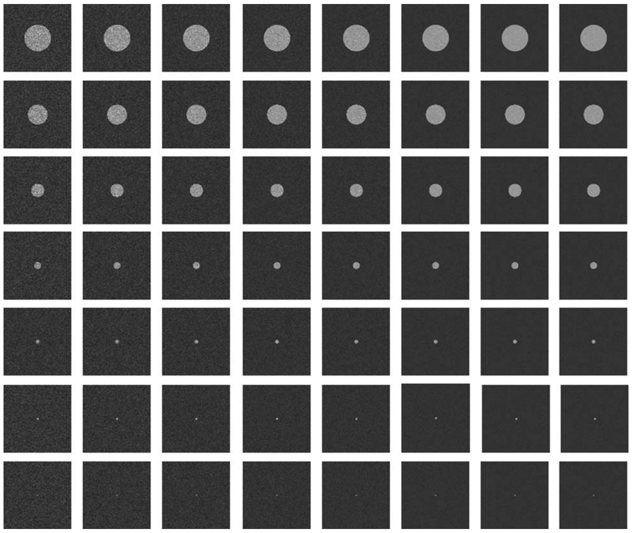

Fig. 2 Synthetic test images.

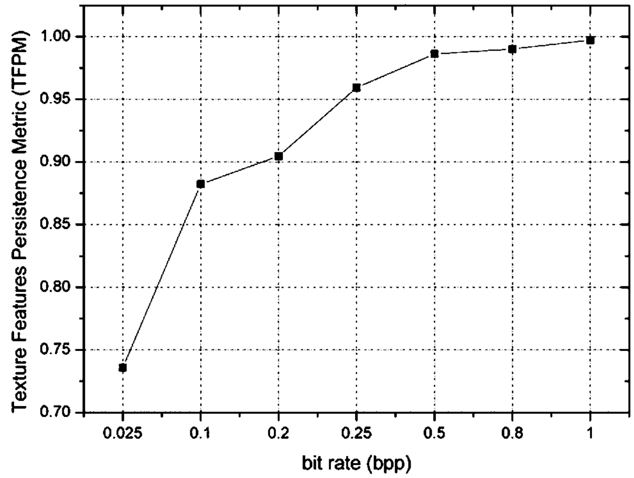

Fig. 3 TFPM versus bit rate.

$$f_{\tilde{S}}(x,y) = \bigcup_{i=1}^{N} f_{\tilde{p}_i}(x,y). \tag{1}$$

For the membership of a point (x,y) in fuzzy set $\tilde{S}$, it is reasonable to select the maximum of all memberships of this point in fuzzy sets $\tilde{p}_i$, which are fuzzed by all points in set S. That is,

$$f_{\tilde{S}}(x,y) = \max_{i \in [1,N]} f_{\tilde{p}_i}(x,y). \tag{2}$$

2.2 *Similarity Metric between Two Shapes*

For a model-based shape matching process, template shape M and shape I are point sets as follows:

$$M = \{M_i | M_i = (x_{M_i}, y_{M_i}),\ i = 1,2, \ldots ,M\},$$

$$I = \{I_i | I_i = (x_{I_i}, y_{I_i}), \quad i = 1,2, \ldots ,N\}.$$

Shape M is fuzzed to be fuzzy set $\widetilde{M}$, then the similarity metric from shape I to the shape M is defined as

$$f_{\widetilde{M}}(I) = \bigcap_{i=1}^{N} f_{\widetilde{M}}(I_i), \tag{3}$$

where $f_{\widetilde{M}}(I_i)$ is the membership of the point I_i in fuzzy set $\widetilde{M}$.

In the application of the shape similarity metric, it is inappropriate to use the commonly-used MIN operator in AND operation. It is possible that there are some noisy points of shape I very far from all points of shape M, that is, they have very low membership values in fuzzy set $\widetilde{M}$. If the lowest membership value is selected to be the similarity metric from shape I to shape M, and the most points of shape I with the higher memberships are not considered, then this approach is unacceptable. Considering all points of the shape, we set the average value of memberships as directional similarity metric *SM(I, M)* from shape I to shape M. That is,

$$SM(I,M) = f_{\widetilde{M}}(I) = (1/N) \sum_{i=1}^{N} f_{\widetilde{M}}(I_i). \tag{4}$$

2.3 *TFPM after Image Compression*

As Fig. 1 shows, to measure the extent to which target texture features are preserved after image compression, the TFPM between source image I_{source} and degraded image $I_{\text{codec-}i}$ after the i'th compression scheme is defined as

$$TFPM_i = TFPM(I_{codec-i}, I_{source}) = SM(S_{codec-i}, S_{source}). \tag{5}$$

3 Experimental Results

To be objective and general, we generate a set of synthetic test images for experiments such as Ref. 8, with various object sizes and various SNR. Here we use 256×256 images, with 256 gray levels. The noise-free image is composed of a centered circular disk object with a gray level of 128 on a homogenous background with a gray level of 64. The noise effect is produced by adding zero-mean Gaussian noise to the noise-free image. The test images are shown in as Fig. 2. From up to bottom, we have objects with diameters from 40% of the image width, through 30%, 20%, 10%, 5%, and 2.5% up to 1.25% to 1.25%. From left to right, the horizontal axis presents the SNR from 2, 2.5, 3, 4, 5, 8, up to 10, and noise-free.

The segmentation method in Fig. 1 can be one of thresholding, region-based, and morphological methods. We select the commonly-used constant false alarm rate thresholding method in the following experiments, in which the false alarm ratio is P_{fa}=0.01. A Sobel operator is selected to implement edge extraction in the following experiments. The membership function $f_{\tilde{p}_i}(x,y)$ can be exponential, trapezoidal, or triangular. To reduce the computation and ensure the robustness of the similarity metric to some extent, we selected a trapezoidal membership function as

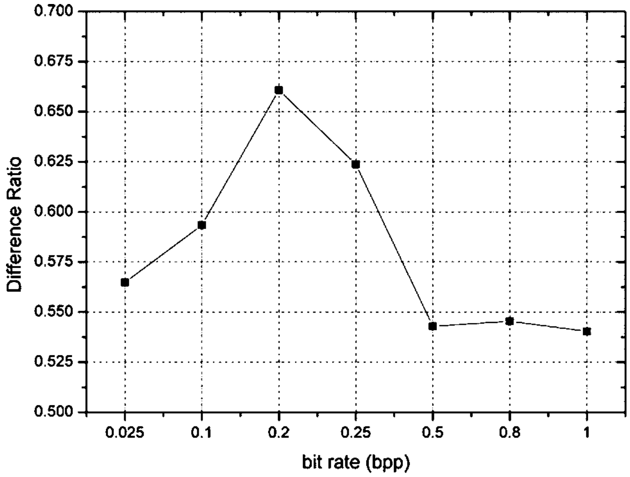

Fig. 4 DR versus bit rate.

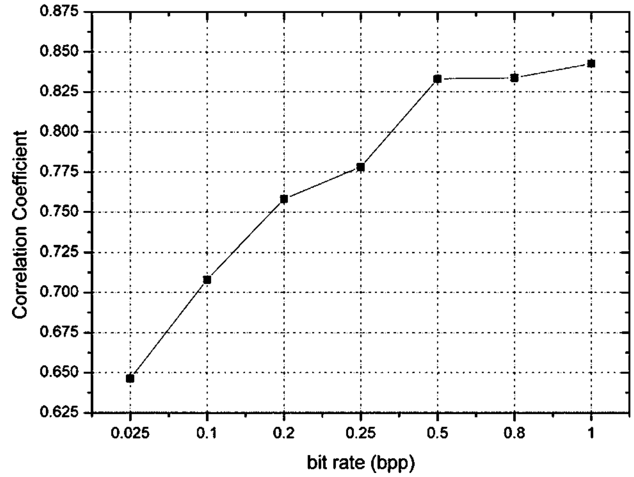

Fig. 5 Correlation coefficient versus bit rate.

$$f_{\tilde{p}_i}(x,y) = \begin{cases} 1 & r \le r_0 \\ \dfrac{t_0 - r}{t_0 - r_0} & r_0 < r < t_0 \,, \\ 0 & r \ge t_0 \end{cases} \tag{6}$$

where $r=[(x-x_i)^2+(y-y_i)]^{1/2}$, t_0 is the upper bound, which means that if the Euclidean distance from point (x,y) to (x_i,y_i) is larger than t_0, point (x,y) has the membership value 0 in the fuzzy set $\tilde{p}_i$. In the following experiments, we set $r_0=1$, $t_0=9$.

The experiment employs JPEG2000 (by Kakadu, v4.5[9]) as the compression scheme, with bit rates from 0.025 to 1.0 bits/pixel. The parameters in this compression tool are set as default.

For an image with fixed object size and fixed SNR, we apply the same segmentation and edge extraction operations on the noisy image and compressed images, and get the TFPM and difference ratio (DR)[4] values as ATR-directed image compression quality metrics. Then we crop the contour shape from the noise-free image to get the template for matching in the edge images produced by compressed images, and get the correlation coefficients to represent the ATR performance.

We consider the TFPM and DR values with the same object size, the same SNR, and various bit rates. When the object diameter is 10% of the image width, and SNR=5, the results of TFPM, DR, and correlation coefficient with respect to bit rate are shown in Fig. 3, Fig. 4, and Fig. 5, respectively. Compared with the DR curve, the TFPM curve shows an increasing tendency, a behavior very similar to the correlation coefficient curve. Other test images with different object sizes and different SNR exhibit similar behaviors. From this standpoint, we conclude that TFPM indicates the edge-matching ATR performance to some extent.

4 Conclusions

We propose a quality evaluation system framework and a novel texture feature persistence metric based on shape similarity for ATR-directed image compression. We believe that the TFPM preferably measures the impact of lossy compression on ATR performance, especially for texture-based target recognition applications. This idea is valuable for future research on ATR-directed image/video coding applications.

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