An Automatic Location Algorithm for Low SNR Moving Targets Based on Adaptive Template

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Abstract SNR is used to analyze target gray characters to its neighbor pixels. According to these low SNR moving puny targets, an adaptive template matching method has been proposed to extract these targets by part Hausdorff distance in measuring the similarity between the templates and target images. Then combined with adaptive thresholding technique, targets precision pixel dimensions can be calculated in given pictures. Critical experiments results of different target images sequences show that this algorithm is fast, stable and flexible with much reference value in related Automatic Target Recognition and location fields.

Keywords Low SNR; Adaptive template; Part hausdorff distance; ATR
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0 Introduction

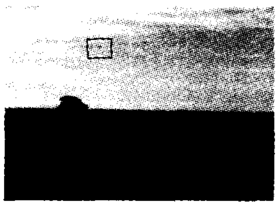
In automatic target recognition (ATR) and location fields, various algorithms have been developed and applied to different types of targets. In respect of the image processing principles, they can be loosely divided into three main groups: 1) edge-detection-based approach[1], which requires targets always occupy certain percent of pixels in image pictures; 2) image segmentation method in that target sub blocks and backgrounds can be extracted by their successive image characteristics[2]; 3) template matching way to recognize and locate targets so long as templates and target sub blocks match under a given similarity measuring criteria[3]. When target and backgrounds verify randomly, template matching way proves its advantages as compared with the former two.

However, if targets are of low SNR and changing during their duration period, fixed templates could diminish while matching target sub blocks. So templates could be chosen adaptively and updated necessarily in order to cope with low SNR puny targets within complex backgrounds. Thus demands similarity measuring criteria adjust to backgrounds and noises interfering.

In this paper, an adaptive template matching method has been proposed to extract above targets by part Hausdorff distance in measuring the similarity between the templates and target images. Then combined with adaptive threshold technique, targets precision pixel dimensions can be calculated in given pictures. Critical experiment results of different target image sequences show this algorithm is fast, stable and flexible with much reference value in related Automatic Target Recognition and location fields.

1 Features of low SNR moving targets

In practical application, digital CCD TV theodolite will record target images at 60 fps from different positions because of the limitations of landforms and system measuring precision requirements under windy or cloudy weathers. Continuous targets fly into sight with a speed of about 300 m/s. After transformation of digital image collection card, a $M \times N$ (e. g., 648×484) sized with 256 gray degrees BMP type (selectable) target images are produced as the follows


(a)Primitive target picture


(b)Gray inversed target picture

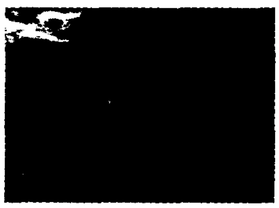

(c)Threshold target picture

Fig. 1 Target pictures

In picture (a), the rectangular area is target sub block. Obviously, the background is made up of random clouds, complex landforms and nature shininess. Moreover, given targets occupy little

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number of pixels are that less than one thousandth of the total full picture pixels. After gray inversion in picture (b), target can be seen as 'bright' puny fleck. If processed by adaptive threshold, this puny fleck is annihilated.

Let I_s represents the signal of target and I_{sb} for target sub block, then the SNR[4] of target pixels to its neighbor ones is

$$\text{SNR}=10\log\left|10+\frac{|I_s|^2}{|I_s-I_{sb}|^2}\right| \tag{1}$$

Where SNR $\in$ (10.2 dB, 10.5 dB) in statistics.

Consequently, this type of target is of typical low SNR moving puny features where efficient template matching method needs to be found.

2 Automatic target location algorithm

2.1 Selection of primitive template

As described in chapter 1, primitive template could be selected adaptively. Take Fig. 2 and Fig. 3 for examples.

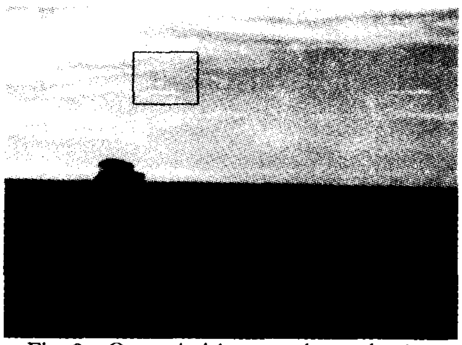

Fig. 2 One primitive template selection

Fig. 3 Another primitive template selection

According to target positions, background features and computation flexibility, $T\times T$ sized primitive template chosen among 16×16, 32×32, 64×64 and 128×128 series in pixels.

2.2 Updating of matching template

Besides, in the target flying duration, primitive template may fail to match all the following target images if backgrounds and noises overpass the target signals. Given that the nearest previous target image correlates the current one in pixels most closely, primitive template can be updated by the former matched target image pixels within $T\times T$ sized target sub block $R_{T\times T}$. This updating method of matching template circles until the end of the image sequence.

2.3 Part Hausdorff distance

Nevertheless, similarity measuring criteria is robust for above matching way is another important problem for ATR. Namely, there are Sum of Matching Error, Mean Square Error[5], Normalized Correlation[6], Ideal Video Similarity, Voronoi Video Similarity[7] and so on. But they are all sensitive to background noise, sheltered target and image distortion. Due to that Part Hausdorff distance is a type of distance measuring criteria regardless of the points correlation in two point sets, it is taken to measure the similarity between templates and images[8].

For two point sets $A=\{a_1,a_2,\cdots,a_p\}$, $B=\{b_1,b_2,\cdots,b_q\}$, Hausdorff distance of A and B is

$$D_{\text{Hausdorff}}(A,B)=\max\left(d_{\text{Hausdorff}}(A,B),\ d_{\text{Hausdorff}}(B,A)\right) \tag{2}$$

Above, $d_{\text{Hausdorff}}(A,B)$ means forward Hausdorff distance from A to B, $d_{\text{Hausdorff}}(B,A)$ for backward Hausdorff distance from B to A

$$d_{\text{Hausdorff}}(A,B)=\max_{a\in A}\min_{b\in B}\|a-b\| \tag{3}$$

$$d_{\text{Hausdorff}}(B,A)=\max_{b\in B}\min_{a\in A}\|b-a\| \tag{4}$$

with $\|\cdot\|$ is Euclidean distance.

Here $d_{\text{Hausdorff}}(A,B)$ is the maximum minimum distance d of points in set A to all the points in set B and there are at least one points in set A whose distances are no larger than d. Furthermore, these points are the 'Most non-matched points', via verse. In short, Hausdorff distance measures the 'Most non-similarity' of two given point sets.

Unfortunately, Hausdorff distance is still sensitive to noise, sheltered target pixels and image distortion. Then part Hausdorff distance has been proposed to solve this disadvantage by comparing only part of the points in two sets[9]

$$D^{k,l}_{\text{Hausdorff}}(A,B)=\max\Big(d^k_{\text{Hausdorff}}\underset{1\le k\le p,1\le l\le q}{(A,B)},\ d^l_{\text{Hausdorff}}(B,A)\Big) \tag{5}$$

In which $d^k_{\text{Hausdorff}}(A,B)$ and $d^l_{\text{Hausdorff}}(B,A)$ are respectively part forward Hausdorff distance and part backward Hausdorff distance

$$d^k_{\text{Hausdorff}}(A,B)=k^{th}_{a\in A}\min_{b\in B}\|a-b\| \tag{6}$$

$$d^l_{\text{Hausdorff}}(B,A)=l^{th}_{b\in B}\min_{a\in A}\|b-a\| \tag{7}$$

Where th denotes the increasing sequencing of $d^k_{\text{Hausdorff}}(A,B)$ and $d^l_{\text{Hausdorff}}(B,A)$ sequences. So, by adjusting k and l, only partial points of set A and set B are computed in given template matching[10].

In addition, in template matching point sets changes in image sequence, k and l can not be fixed numbers and they must be normalized to percentages[11]

$$k=f_1\times p, l=f_2\times q, 0\leqslant f_1\leqslant 1, 0\leqslant f_2\leqslant 1 \quad (8)$$

The next is to decide whether

$$d^k_{\mathrm{Hausdorff}}(A,B)\leqslant \tau_k, d^l_{\mathrm{Hausdorff}}(B,A)\leqslant \tau_l \quad (9)$$

τ_k and τ_l are preset thresholds.

By now, based on the part Hausdorff distance template matching, these low SNR moving puny targets have been recognized.

2.4 Location of the targets

Though part Hausdorff distance is not sensitive to backgrounds and noises, in target location, ways should be found to decrease their influences. Supposed, template matching is refined to target $S\times S$ sized sub block $R_{S\times S}(S>T)$, with pixel (x,y) gray degree $G(x,y)$, the average gray degree Thr is introduced[14]

$$Thr=\frac{1}{S^2}\sum\sum G(x,y), (x,y)\in R_{S\times S} \quad (10)$$

Threshold pixel gray degree $g(x,y)$ is functioned

$$g(x,y)=\begin{cases}1 & G(x,y)>Thr\\ 0 & G(x,y)\leqslant Thr\end{cases}, (x,y)\in R_{S\times S} \quad (11)$$

Then target precision pixel dimensions (x^t, y^t) in current matched image, target point dimensions, can be calculated in Eq. (12) and Eq. (13)

$$x^t=\frac{\sum x\cdot g(x,y)}{\sum g(x,y)}, (x,y)\in R_{T\times T} \quad (12)$$

$$y^t=\frac{\sum y\cdot g(x,y)}{\sum g(x,y)}, (x,y)\in R_{T\times T} \quad (13)$$

Above all, target recognition and location are accomplished by this automatic algorithm.

3 Efficiency of the algorithm

In processing, the algorithm steps are shown as follows:

Step1: Load target image sequence, length n_f, and initialize pointer to image $i=0$.

Step2: Select primitive template.

Step3: Template matches within sub block $R_{S\times S}$.

Step4: Calculate part Hausdorff distance $d^k_{\mathrm{Hausdorff}}(A,B)$ and $d^l_{\mathrm{Hausdorff}}(B,A)$.

Step5: Decide whether $d^k_{\mathrm{Hausdorff}}(A,B)\leqslant\tau_k$ and $d^l_{\mathrm{Hausdorff}}(B,A)\leqslant\tau_l$, if Yes, compute target precision pixel dimensions and update matching template; Else, $i++$, go to Step6.

Step6: Judge $i\leqslant n_f$, if Yes, go to Step2; If No, end processing.

Probably, when applied to these low SNR puny targets, this algorithm might fluctuate, so its real efficiency should be evaluated.

If there are N targets to be processed every experiment, for each target only S_k points can be recognized and calculated, so the mean location error σ_p in pixel evaluated[15]

$$\sigma_p=\frac{\sum_{i=1}^{N}\sum_{j=1}^{S_k}\sqrt{(x^t_{ij}-x^0_{ij})^2+(y^t_{ij}-y^0_{ij})^2}}{\sum_{k=1}^{N}S_k} \quad (14)$$

In which, x^t_{ij}, y^t_{ij} denote respective calculated target point dimensions by Eq. (12) and Eq. (13), x^0_{ij}, y^0_{ij} are the theoretical target point dimensions and $\sigma_p\sim N(\mu,\delta^2)$, with $\mu=0.25$, $\delta^2=1.5^2$ limited by this algorithm. Meanwhile, the target points location percent η is

$$\eta=\frac{\sum_{k=1}^{N}S_k}{N^2}\times 100\% \quad (15)$$

Desired: $\eta\sim\mu[90\%, 100\%]$.

Additionally, the average processing time T_a got in ms

$$T_a=\frac{\sum_{l=1}^{N}T_l-\sum_{l=1}^{N}T_l^M}{N} \quad (16)$$

Defined: T_l is the whole processing time for each target, T_l^M represents the time clicking algorithm buttons.

4 Experiment results & conclusion

This algorithm is programmed under OS Microsoft Windows 2000 Professional (Service Packet 3) with Microsoft Visual C++ 6.0 (English Version). Operated by different researchers for two image sequences under diverse hardware platform statuses, results are shown in Tab. 1.

Tab. 1 Experiment results of the algorithm

Platform	Image sequence	N	$\frac{\sum_{k=l}^{N}S_k}{N}$	σ_p	$\eta(\%)$	T_a/ms
A	Ⅰ	4	3.9	1.3	97.5%	65.3
B	Ⅱ	18	17.2	1.4	95.6%	55.2
C	Ⅰ	4	3.9	1.2	97.5%	29.3
C	Ⅱ	18	17.2	1.3	95.6%	21.2

A: Assembled PC, Intel 1.7 GHz P4 CPU, 512MB DDR266 SDRAM, Ultra ATA 100 Hard disk, 7,200 rpm.

B: Assembled PC, Intel 2.4 GHz P4 CPU, 512MB DDR400 SDRAM, Serial ATA 133 Hard disk, 7,200 rpm.

C: Dell Graphic Workstation, Intel 2.4GHz Xeon CPU, 1.0GB DDR266 SDRAM, Ultra 320 SCSI Hard disk, 10,000 rpm.

Ⅰ: Pictures on Land, Sequence Length = 383 Frames; Ⅱ: Pictures by Water Areas, Sequence Length = 2095 Frames.

From Tab. 1, conclusion can be drawn that this automatic location algorithm for low SNR moving targets based on adaptive template is fast, stable and flexible.

If attached with Region-splitting Technique[12] and Progressive Threshold[13], this algorithm can be used in other real-time processing fields, such as automatic target tracking. In a word, it is of much reference value in Automatic Target Recognition and location applications.

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基于自适应模板的低信噪比运动目标的自动定位算法

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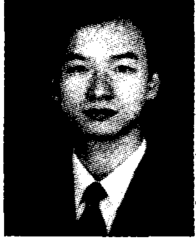
摘　要　从目标相对于邻域背景区的信噪比出发,分析了其低信噪比运动小目标特性对自动目标识别所带来的困难.基于部分 Hausdorff 距离在模板匹配相似性度量中可以有效抑制背景与噪声干扰的优点,提出了用自适应模板实现自动目标识别的方法.然后,综合目标区像素灰度自适应二值化处理和形心算法,实现了图像序列中目标自动定位的功能.实验结果证明:该基于自适应模板的低信噪比运动目标的自动定位算法具有快速,稳定和实用等优点.

关键词　低信噪比;自适应模板;部分 Hausdorff 距离;自动目标识别



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