Optimization of OT-MACH filter generation for target recognition

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ABSTRACT

An automatic Optimum Trade-off Maximum Average Correlation Height (OT-MACH) filter generator for use in a gray-scale optical correlator (GOC) has been developed for improved target detection at JPL. While the OT-MACH filter has been shown to be an optimal filter for target detection, actually solving for the optimum is too computationally intensive for multiple targets. Instead, an adaptive step gradient descent method was tested to iteratively optimize the three OT-MACH parameters, α, β, and γ. The feedback for the gradient descent method was a composite of the performance measures, correlation peak height and peak to side lobe ratio. The automated method generated and tested multiple filters in order to approach the optimal filter quicker and more reliably than the current manual method. Initial usage and testing has shown preliminary success at finding an approximation of the optimal filter, in terms of α, β, γ values. This corresponded to a substantial improvement in detection performance where the true positive rate increased for the same average false positives per image.

Keywords: OT-MACH filter, correlation, optimization, target detection, false alarm reduction

1. INTRODUCTION

Object recognition still attempts to match the human ability to recognize targets in noisy environments. A good system must recognize real targets while minimizing false detections. General filters are crucial in these systems to condense a large image to smaller regions of interest where more specific and computationally intense techniques can then identify targets with better accuracy. JPL has done research into the avenues of target recognition using Grayscale Optical Correlation (GOC) under years of funding from DOD and NASA [1, 2]. One established GOC filter is the Optimum Trade-off Maximum Average Correlation Height (OT-MACH) filter [3]. This optical Fourier filter allows nearly instantaneous calculation of the likely target locations in an image. The filter generalizes well and has the advantageous features of shift-invariance, high speed and parallelism. Computer simulations allow the most flexibility for developing the filter and testing its performance. The simulation uses the Fourier transforms of training images to construct a filter based on the measures of Average Correlation Height (ACH), Average

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Similarity Measure (ASM), Average Correlation Energy (ACE), and Output Noise Variance (ONV). The filter is based on these characteristic measures through the energy function [3]:

$$E(\mathrm{h}) = \alpha(ONV) + \beta(ACE) + \gamma(ASM) - \delta(ACH) \tag{1}$$

The filter equation simplifies since the δ term is mostly insignificant, instead, the filter is based off the α, β, and γ terms. Thus, in choosing different values for these coefficients the filter can have different properties, allowing the OT-MACH filter to be flexible enough to emphasize different features for different types of target images[1-2].

While there is an optimal α, β, and γ value for a given training set, it is unfeasible to solve this analytically. Currently a manual solution is used to estimate the necessary changes in α, β, or γ to achieve improved detection rates. This approach finds solutions but is time consuming and requires a user repeating an iterative process.

Selection of *α, β*, and *γ* can be automated to speed up and improve the performance of the OT-MACH [4]. The goal of the automated program is to approach the optimal trade-off values of *α*, *β*, and *γ* in as few iterations as possible. The program approaches the optimum through an adaptive step gradient descent algorithm. The optimization is measured by the performance metrics of Correlation Peak Height (PK) and Peak-to-Side lobe Ratio (PSR) which are associated with the filter's target detection in true positive rate and false positive reduction [5].

2. OPTIMIZATION APPROACH

The approach taken to automate the filter generation process was to select the training images and properly size them to perform a correlation with a test image [6]. This training image creation process is shown in Figure 1 below.

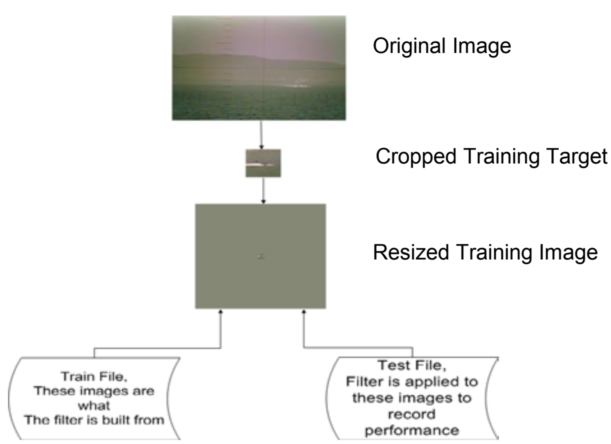


Figure 1: *The process for training image preparation and classification.*

From these training images half are used to generate the filter using initial seed values for α, β, and γ. An incremental constant is added these values to measure the effect on the performance metrics in order to use the adaptive step gradient descent algorithm. The derivative is assumed to be linear since the change in α, β, and γ is small. The performance measures are calculated by testing the newly generated filters on the other half of the trained images, the ones not used to build the filter. The filter is correlated with the test images and the performance score is counted from the known target position from the test images. In order to reduce the performance score to a single metric the Correlation peak and PSR measures are combined in an equation favoring optimization of the peak value. The adaptive gradient descent algorithm maintains a user input minimum PSR threshold while the peak score is optimized. The increased peak score benefits the true positive rate at the cost of an increase in false positives. A higher PSR score makes the filter better able to discern between true positives and false positives. In some alternate cases, the filter can be optimized via PSR values, while retaining a minimum Peak value.

The performance measures of Correlation Peak and PSR are used to calculate a first order derivative that is used in the gradient descent algorithm to calculate new values for α, β, and γ. The algorithm repeats this process again using the same training images except this time with the new values for α, β, and γ rather than the seed values. This loops through a set number of iterations as the filter is optimized by gradient descent [6]. A flow chart of the filter generation and optimization process is shown in Figure 2.

Sometimes the OT-MACH filter optimizer converged to a local maximum, leaving room for error; thus a more detailed examination was needed to find the best filter [3]. To see the relationship between the OT-MACH parameters α, β, and γ, and the correlation Peak height and PSR values, a permutation method was run that tested a broad set of parameter values and graphed the results for easy recognition. The method holds one parameter constant while it varies the other two and graphs the corresponding output, as shown in Figures 3 and 4. The peak location indicates the global optimal values of the OT-MACH parameters α, β, and γ, as measured by the highest PSR value.

Once a performance method was chosen, the parameter starting values were obtained by approximating the plots in Figures 3 and 4. The final values for the filters were obtained by using the Filter Optimization program. After the performance characteristics were set, the local region of optimization was chosen.

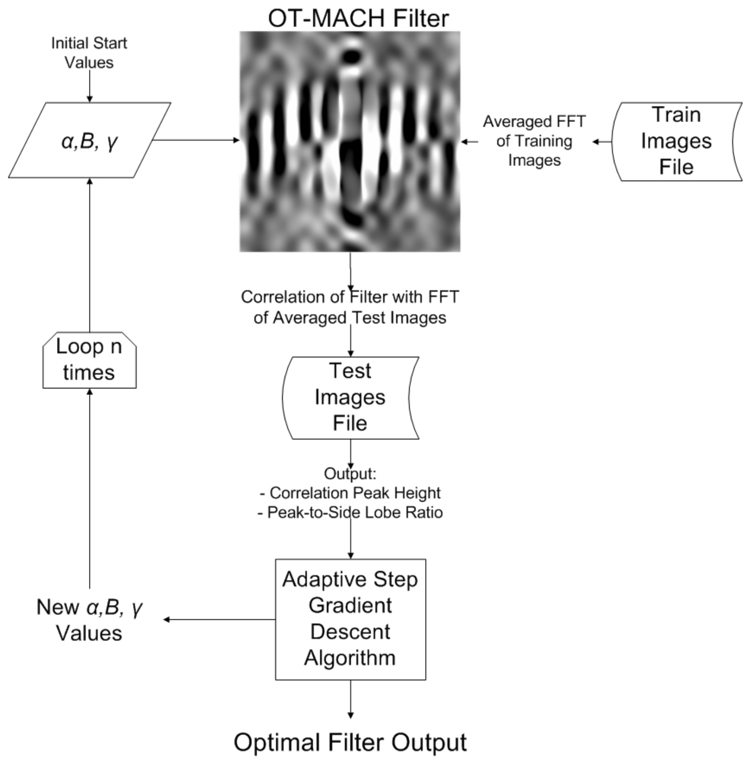


Figure 2: *The OT-MACH automated filter generator and α, β, γ optimizer.*

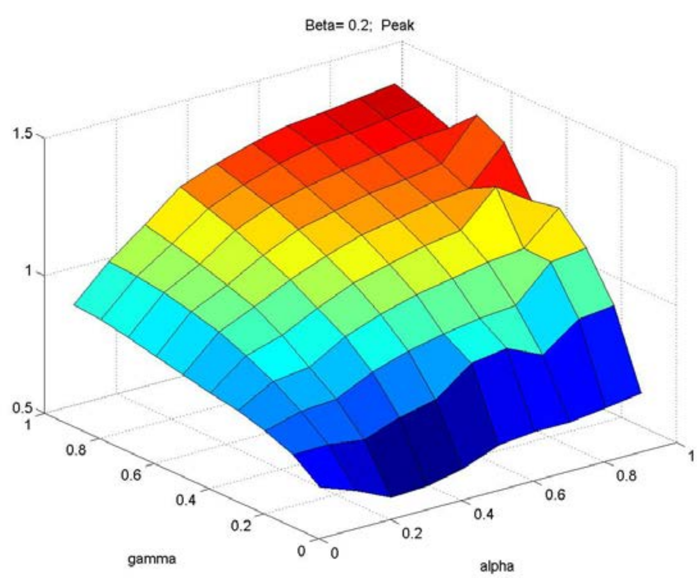


Figure 3*: 3-D plot of Peak Value vs. Alpha vs. Gamma with constant Beta*

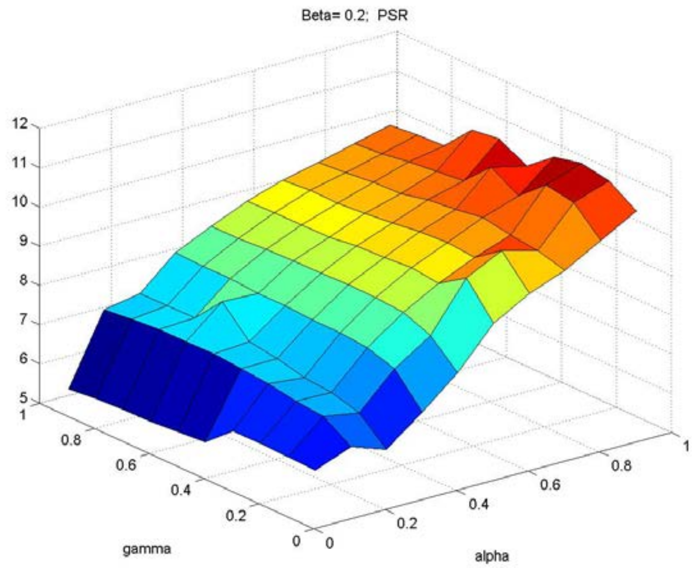
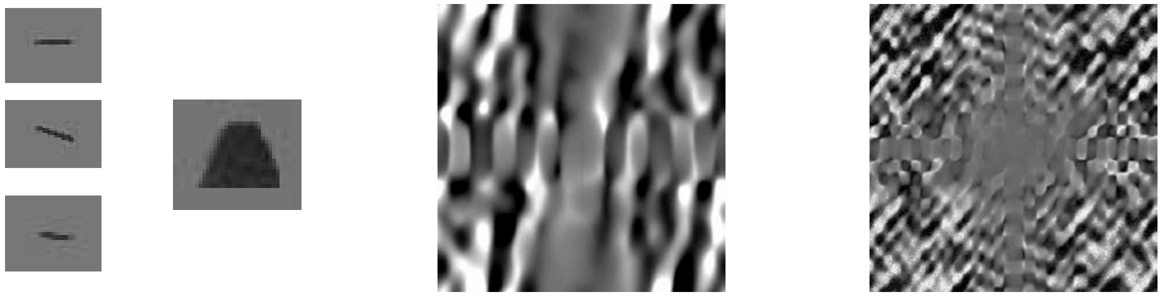


Figure 4: *3-D plot of PSR Value vs. Alpha vs. Gamma with constant Beta*

3. TEST RESULTS

The automated OT-MACH filter generator algorithm was then used on real test data of a video sequence of jet firing a missile, as shown in Figure 5. The video was around 40 frames long and the missile changed orientation relative to the jet. Each image was 484x326 pixels. The training images used in the filter generation were the models of the missiles and jet tail fin with different angle orientation and sizes, as shown in Figures 6(a) and (b). The automated optimization algorithm was run for building a filter with optimal values for α, β, and γ. The OT-MACH filters are shown in Figures 6(c) and (d).

Figure 5: *A video sequence of a jet firing a missile is used as a set of test image.*



(a) (b) (c) (d)

***Figure 6**: Training of the OT-MACH filters: (a) training images of the missile; (b) a training image of the tail fin of the jet; (c) the OT-MACH filter of the missile; (d) the OT-MACH filter of the jet.*

The automated OT-MACH filter generator algorithm was then used on the test video sequence to detect, identify and track both the jet and the missile in real-time. The performance results are shown in Figures 7 and 8. The jet and the missile are correctly identified. But there are false positives, as shown in Figure 7. Table I shows the optimized parameters and the performance of the filters. By applying intelligent thresholds using a trained neural network [2], we were able to further reduce the false alarms, as shown in Figure 8.

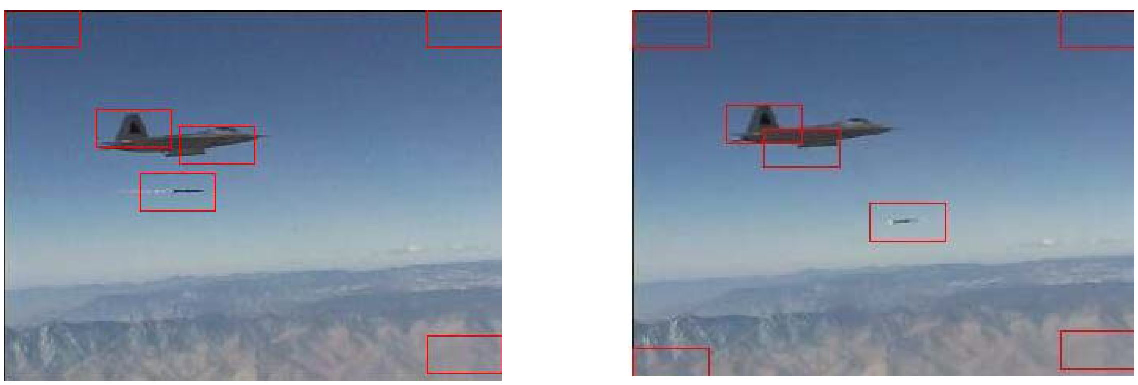


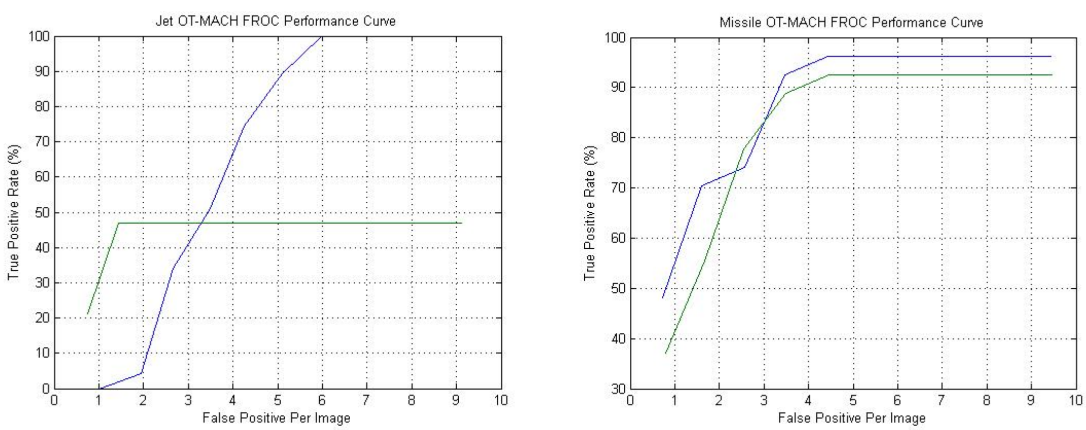
***Figure 7:** Detection of the jet and the missile. False alarms in the boundary can be eliminated.*

***Figure 8:** After post-processing, the jet and the missile are correctly identified. False alarms are eliminated.*

Table I: Optimized Filter Parameters for Jet and Missile

Parameter	**Jet**	**Missile**
α	0.92	0.5828
β	0.4281	0.8295
γ	0.799	0.2439
True Target Detection Rate (%)	100	96.3
False Positive Per Image	6	4.5

After the optimal filter was selected based on its combined performance score, the filter was tested using a Frequency Relative Operating Characteristic (FROC) curve, plotting the average false positives per image against the True Positive Rate (TPR). The strength of target recognition is based on the performance scores of peak and PSR. Setting these thresholds allows us to determine how tight the thresholds to be considered a target are in order to maximize TPR while minimizing false positive average. In Figure 9, two FROC curves are generated for each target, one uses the filter generated with initial values (α, β, γ) = (0.5, 0.5, 0.5); and the other curve is the performance using the filter with optimized parameters shown in Table I.



(a) (b)

Figure 9*: FROC curve of (a) jet and (b) missile, using filters with both initial and optimized* α, β, and γ.

In another test of a video sequence, several filters were saved and tested to display progression over the number of iterations of the algorithm in the detection improvements using the FROC curve. The median values were derived from running a permutation method that sampled many combinations of α, β, and γ and their filter's corresponding performance score. The three median scores were plotted and the median 1 curve in Figure 10 was used as the start point for the filter optimization algorithm. This shows that optimizing the composite Peak and PSR gradient descent-based algorithm will lead to improved detection performance and leads to filters with substantially better detection rates.

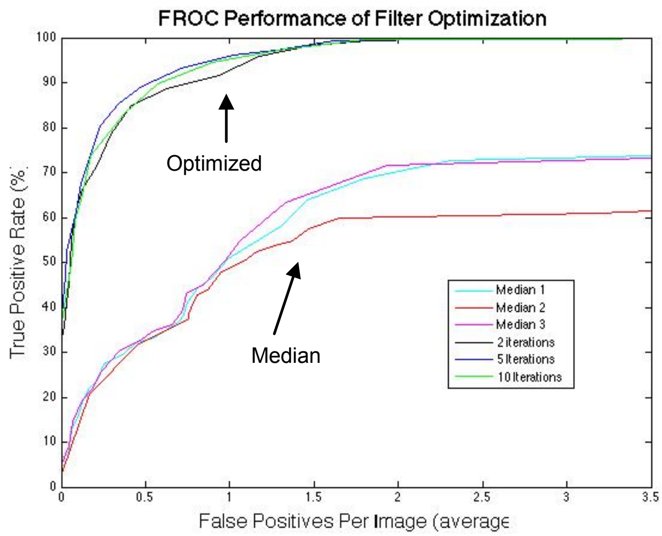


Figure 10: *The improvement in detection and false positive reduction from the algorithm using median values of the parameters and the optimized* α, β, and *γ values.*

4. DISSCUSSIONS AND SUMMARY

The automated OT-MACH filter generator was shown to produce and improve filters from training images set. The filter generator algorithm ran iterations to optimize the filter that was able to achieve a higher TPR, which will be substantially reduced in passing the filtered data to a neural network for verification and further false positive reduction [2]. We have studied the optimization process of the relationship between the composite peak and PSR optimization and also the FROC curve detection rates. The performance progression was measured from many initial α, β, and γ values in order to get a statistically significant global measure of the detection improvement.

The OT-MACH filters could be entirely automated and would store a bank of general simulated models to target. Upon the possible sighting of one of these targets the algorithm would use the image found to automatically create and optimize real-time a filter specific to that target to take advantage of a more precise and accurate filter than the general filter. The OT-MACH filter is widely adaptable and flexible enough to deal with a wide range of possible datasets. The filter could periodically update to stay current with the target as well as having programmed checkers to verify it is a target and not false positive. This sort of online adaptive OT-MACH filter system is possible with a general automated filter generator.

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