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A Survey on Correlation Filter and its Applications

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Abstract: **Correlation filters will find applications in pattern recognition such as biometric recognition, object alignment, action recognition, object detection and tracking. The advanced correlation filters were introduced to offer distortion-tolerant object recognition. The recent major advance in correlation filter design is zero-aliasing correlation filters (ZACFs) that eliminate the aliasing in correlation filter design due to the circular correlation caused by the use of discrete Fourier transforms (DFTs).**

Index Terms- **Correlation Filters, Aliasing, Circular Correlation**

I. INTRODUCTION

Humans can easily recognize any object, numbers, alphabets, voices, faces, scene, vehicle, houses, roads etc. However, making a computer to recognize these types of objects is a challenging task. Pattern recognition plays an important role in diverse fields and it is an area of artificial intelligence. Correlation filters (CFs) have been successfully applied to a variety of pattern recognition applications including automatic target recognition (ATR) and biometric recognition. Correlation is a natural metric for measuring the similarity between a reference pattern and a test pattern [1]. This filter can be viewed as a kind of classifier which is commonly used for different pattern recognition tasks. Generally speaking, a correlation filter is a template that is specifically designed based on a set of training images, which come from both an authentic class and the non-authentic classes. When this correlation filter is correlated with a query image, a correlation peak is obtained if the query image comes from the authentic class, while the correlation of the peak is not sharp if the query image belongs to the non-authentic class [2].

II. CORRELATION FILTER

Correlation filters can be broadly classified in to three groups: equality constrained CFs, unconstrained CFs, and inequality constrained CFs. The MACE filter [3] is an example of equality constrained CF where the dot products between the training images and the template are constrained to equal some pre-specified values. The MOSSE filter [8] is an example of an unconstrained filter that minimizes the localization loss between a desired correlation output shape and the actual correlation output. Finally, MMCF [11] is an inequality constrained filter that leverages ideas from support vector machines (SVMs) to achieve better recognition. Although we discuss only a small subset of CFs, similar derivations can be obtained for other

A. Minimum Average Correlation Energy Filter

The MACE filter [3,4] is the first filter designed to control both the shape and the peak of the correlation plane. This can be achieved by minimizing the average correlation energy (ACE) of the correlation plane from the training images. The MACE filter facilitates recognition by producing very sharp delta-function-like peaks with minimum side lobes for authentic class training images and no such sharp peaks for unauthentic class.

B. *Optimal tradeoff synthetic discriminate function filter (OTSDF)*

The OTSDF filter [5,6] is widely used. Minimizing the average correlation energy leads to high-frequency emphasizing filters whereas minimizing output noise variance leads to low-frequency emphasizing filters. Thus minimizing one criterion significantly deteriorates the performance from the point of view of the other criterion. An optimal filter is defined such that for a given value of average correlation energy, the output noise variance is minimized and vice-versa.

C. Maximum average correlation height filter (MACH)

MACH filters are developed for better recognition performance. It is designed to minimize the average similarity measure, i.e., the scatter of the correlation planes, and simultaneously minimize the average correlation energy and maximize the average correlation peak intensity. Savvides and Kumar, *et al.*[7] proposed that the unconstrained MACE filter can be efficiently trained online and adapt to varying data streams caused by changes in illuminations, backgrounds, and different views.

D. Extended maximum average correlation height filter (EMACH)

MACH sometimes fails to capture the finer details of the desired class because the average of training images sometimes looks like a clutter image. Thus MACH may be difficult in discriminating the desired class from the clutter. Thus EMACH filter is used to improving this clutter rejection capability. For this it measure modified ASM that capture finer details of the training set and makes the EMACH filter more sensitive against clutter.

E. Minimum output sum of squared error filter (MOSSE)

This filter is designed to minimize the mean squared error between the desired correlation plane and the actual correlation plane. MOSSE filter [8] adapt in real time to changes due to rigid-body motion, deformation and lighting. The filter adapts by weighting new images more, with weight for older images decaying exponentially over time.

F. Maximum margin correlation filter

A recent breakthrough in CF design is maximum margin correlation filters [9]. MMCFs combine the excellent localization properties of CFs with the very good generalization abilities to support vector machines. Traditionally, constrained CF designs are constrained such that the dot product of a training image and the CF template is set to a specified value. In the MMCF formulation, however this hard constraint is removed and is replaced with an inequality constraint instead; the dot product of a training image and the CF template must be larger than or equal to some value. MMCF is designed as a tradeoff between maximizing the distance between the hyper plane and the data points and minimizing the ACE in order to have a sharp peak in the correlation output.

III. ZERO-ALIASING CORRELATION FILTER

In the frequency domain, correlation may be represented as an element-wise multiplication between the DFTs of two signals. However, it is well known that multiplying two DFTs together results in a circular correlation, rather than a linear correlation. In the past, CFs have been formulated with this element-wise multiplication, which implicitly assumes a circular correlation. However, CFs are applied to test data using linear correlation. Therefore, there is an inconsistency between how CFs are designed and how they are applied.
This problem was first explored by Sudharsanan, *et al.*[14] in which the well-known MACE filter was reformulated in the space domain. While this CF avoided circular correlation effects, it required a cumbersome formulation that was very inefficient to compute. Despite this work, the circular correlations in CF design were largely assumed to be approximately the same as linear correlation, and, as such, CF designs over the years continued to ignore the circular correlation issues in their frequency domain formulations. Recently, Rodriguez *et al.*[13] explored several different methods to reduce circular correlation effects during CF design. These methods include various methods of padding training images or windowing training images to reduce edge effects. However, none of the methods presented adequately deal with eliminating circular correlation. In 2015, Fernandez *et al.*[15] introduced a solution to the long standing problem of circular correlation in CF designs. This solution, known as zero-aliasing correlation filters (ZACFs) which imposes zero-aliasing constraints on the CF design to ensure that the multiplication of DFTs in the frequency domain does in fact correspond to a linear correlation.

To fix the circular correlation problem, we introduced hard constraints on the CF design that force the tail of the template to zero. We require that training images are padded and a DFT of size 2d-1 is used. By zero-padding training images and imposing constraints on the filter design, we obtain a template that is all zeros in the tail. The element-wise multiplication of the DFT of this template with DFTs of padded training images corresponds to a linear correlation, rather than a circular correlation.

IV. APPLICATIONS OF CORRELATION FILTER

Correlation filters (CFs) are well established and useful for a variety of tasks in signal processing and pattern recognition. In these applications, we attempt to extract information from signals of different types. These may be one-dimensional (1D) signals (usually time-varying waveforms); for example, a heartbeat signal, a wireless communication signal, or a speech waveform. More often, the signal is a two-dimensional (2D) image in which we attempt to detect objects or patterns. CFs can also be applied to three-dimensional (3D) signals (videos), to detect a particular type of motion, e.g., action detection. In principle, CFs can be applied to signals of any dimensions, except that the computational and memory complexities grow significantly with increased signal dimensionality.

A. 1 Dimensional applications In signal and audio processing

Mainly focuses on signal characteristics, detection and identification.

a. Detection and estimation of periodic signals in random noise

Many signals on communication lines suffer noise interruption problems. The random noise can be identified from the noise corrupted signal which is received by the receiver, by computing the auto correlation function [16].Example for this detection is QRS signal detection from ECG waveform.

b. Identifying information carrying signal from random noise

In addition to the identification of noise signal correlation can be used to identify the exact localization of information signal [16].

c. Estimation of power spectral density

The Fourier transform of the auto correlation function of an energy signal is called power spectral density. The PSD is powerful for detecting periodic components in data and identifying the dominant power [16].

B. 2 Dimensional applications: In image processing

Mainly focuses on image processing applications. The basic information regarding the physical properties can be extracted from the change of intensities and the localization of edges [16]. For this correlation filter techniques is used for easy and speedy analysis. In this correlation filter performs as box type filter.

a. Alphabetic character recognition using correlation maxima

A series of images have been converted into an avi file, each image as a frame. The created video file runs these images one by one with a time delay. The target image is compared frame by frame, alphabet by alphabet by computing 2D correlation and its maxima. The alphabet with highest maxima is considered as output.

b. Sharpening of colored image using luminance processing with 2D correlation filter

The colored RGB image is converted to Y'CbCr format. This has been made intentionally blurred using averaging correlation filter. The intensity layer of image has been processing by a high pass correlation filter and then converted back to its RGB form. The output image shows two levels of sharpening [16].

c. Edge detection with correlation integral filter

In order to acquire physical features of an object the human as well as machine vision require measurements of the amount of the reflected light from the object. For this process correlation integral filter [16] is used. It performs correlation filtering of an integral image with an appropriate box type filter.

C. 3 Dimensional applications: video processing

Visual tracking is an important application in video processing. When one target is located in one frame of video,it is easy to track that object or target in subsequent frames [17] Target appearance is modeled by adaptive correlation filter and trackng is performed via convolution. MACE and MOSSE filters are more robust to appearance changes and are better for tracking the object.

V. CONCLUSION

This review successfully described the different types of correlation filters along with various applications in signal, audio, image and video processing applications. The digital correlation filtering methods have been found very useful, easy and simple to understand and implement for many pattern recognition algorithms. The survey described that ZACFs exhibits significantly better performance than the conventional filters by removing the aliasing issue in correlation.

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