A Note on Feature Extraction Based on Kanade-Shi-Tomasi Procedure and Kalman Filters

Tatjana Grbić[1], Aleksandar Jovanović[2], Slavica Medić[1], and Aleksandar Perović[3]

[1] University of Novi Sad, Faculty of Technical Sciences
[2] University of Belgrade, Faculty of Mathematics
[3] University of Belgrade, Faculty of Transport and Traffic Engineering
{tatjana,slavicm}@uns.ac.rs,
aljosha.jovanovich@gmail.com, pera@sf.bg.ac.rs

Abstract. We present a short overview of the portion of our work in the analysis of biological, acoustic, sonar and radar signals, with particular emphasis on the feature extraction using modified Kanade-Shi-Tomasi procedure and the application of Kalman filters. Developed methodology is illustrated with several examples.

Keywords: Automatic detection of spectral features, invariants of signal features, brain-computer interface, noise elimination in radar signals.

1 Introduction

Feature detection and extraction has been a prominent topic in signal processing from its very beginnings. Our interest in this area has started in late eighties with the formulation of initial problems related to brain functionality, especially in detection of specific cognitive activities. The first success was related to detection of imagined tones in early nineties using rather meagre acquisition resources, see [2, 3]. Later our interest varied from integration of digital imaging devices with optical microscopic systems, feature extraction based on photo morphology, various standard and non-standard applications of Fourier spectroscopy, as well as analysis of different causality criteria used in contemporary study of brain functionality.

The body of the related work is rather staggering. Due to the very limited space, we are unable to offer due credit to the research that had significant impact on our work. References [1-8] are pointers to our work where the reader can found detailed presentation of the research topics that we have deal with during the last quarter of the century, while the rest of the references [9-21] contain work of some of our colleagues and collaborators and can be also used as nice reference resources.

The paper offers an overview of the part of our work published in [7] related to extraction of the dot-like objects from heavily contaminated signals. We present two extraction methods that are based on the Kanade-Shi-Tomasi procedure and the so called bank of Kalman filters. Though all testing is carried out on digital images, we

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believe that the offered methodology can be successfully applied in detection and extraction of any kind of features that are both narrow in band and frequency. Related to speech recognition, the offered methods may yield some promising result in automated extraction of some specific sound patterns from the signals with lots of background noise and artefacts.

2 Feature Extraction Based on Intensity Discrimination

In this section we will present the first of the two methods that we have used for the efficient extraction and recognition of dot-like objects with the diameter not greater than 10 pixels. Both methods can be applied to matrices and vectors, which can be used to handle short frequency pulses and spectral features that are stable and narrow in frequency.

The first of the mentioned two recognition/extraction procedures for small objects is based on intensity discrimination of considered pixels. The method itself is an adaptation of the procedure for the extraction of the characteristic features from a bitmap image developed by Shi, Tomasi and Kanade (see [15, 17]).

As an input we have a simple monochrome (0 = white, 255 = black) bitmap (matrix) A of a fixed format (here presented with 400×400 pixel resolution). The components of A can be signal amplitude values, or e.g. spectrogram intensities, and will be denoted by $A(x, y)$. Here x indicates the corresponding row and y indicates the corresponding column. Spatial x-wise and y-wise differences I_x and I_y are defined by

$$I_x = \frac{A(x+1,y)-A(x-1,y)}{2}, I_y = \frac{A(x,y+1)-A(x,y-1)}{2}. \tag{1}$$

The matrix G of sums of spatial square differences is defined by

$$G = \sum_{x=p_x-\omega_x}^{p_x+\omega_x} \sum_{y=p_y-\omega_y}^{p_y+\omega_y} \begin{bmatrix} {I_x}^2 & I_x I_y \\ I_x I_y & {I_y}^2 \end{bmatrix}, \tag{2}$$

where $\omega_x = \omega_y$ is the width of the integration window (the best results are obtained with values between 2 and 4), while p_x and p_y are the indices corresponding to the indices x and y such that the formula (2) is defined. Hence, all so called inner pixels, i.e. pixels for which I_x and I_y are definable, are included in the computation. The more compact form of the matrix G is given by

$$G = \begin{bmatrix} a & b \\ c & d \end{bmatrix}. \tag{3}$$

Consequently, the eigenvalues of G are given by

$$\lambda_{1,2} = \frac{a+d}{2} \pm \frac{\sqrt{(a-d)^2+4bc}}{2}. \tag{4}$$

Moreover, for each inner pixel with coordinates (x, y) we define $\lambda(x, y)$ by

$$\lambda(x,y) = \min(\lambda_1(x,y), \lambda_2(x,y)). \tag{5}$$

Finally, for the given lower threshold $T_{\min}$ and the parameter $A_{\max}$ (in our examples $A_{\max} = 255$) we define $\lambda_{\max}$ by

$$\lambda_{\max} = \max\{\lambda(x,y) \mid (x,y) \text{ is an inner pixel}\}. \tag{6}$$

The extraction matrix E is defined by

$$E(x,y) = \begin{cases} \frac{A_{\max}}{\lambda_{\max}} \cdot \lambda(x,y), & \frac{A_{\max}}{\lambda_{\max}} \cdot \lambda(x,y) > T_{\min} \\ 0, & \frac{A_{\max}}{\lambda_{\max}} \cdot \lambda(x,y) < T_{\min} \end{cases}. \tag{7}$$

With two available images/spectrograms, using described method we can solve harder cases of automatic extraction. Indeed, let B and C be two images where every pixel is contaminated with noise which has a normal Gaussian distribution, in which a stationary signal is injected, objects at coordinates $(x_1, y_1), \ldots (x_{10}, y_{10})$, all with an intensity of e.g. m (within $[0,255]$ interval) and fluctuation parameter p; we generate the new binary image A as follows:

$$A(x,y) = \text{abs}(B(x,y) - C(x,y))$$
$$\text{If } A(x,y) < p \text{ then } A(x,y) = 255$$
$$\text{else } A(x,y) = 0;$$

The above simple discrimination reduces random noise significantly and reveals the signals together with residual noise. By performing the procedure defined by the equations (1) thru (7), we obtain the filtered image with extracted signals. The method is adapted, using two parameters of optimization (minimax): the minimalization of the integral surface of detected objects, then the maximization of the number of the small objects.

In order to illustrate the application of the presented extraction method from the single source, we will present three sample images together with the corresponding extraction images (Fig.1-3). Initial images are formed by initial introduction of several dots (useful signals) with an amplitude of $a = 120$, and then contaminated with the random cloudlike noise.

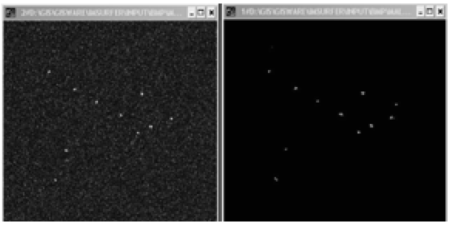

Fig. 1. Noise reduction – first example

The images on the left side show the initial bitmap, while the images on the right side show the corresponding extraction result. In all three examples the initial setting is $A_{\max} = 255$ and $T_{\min} = 124$.

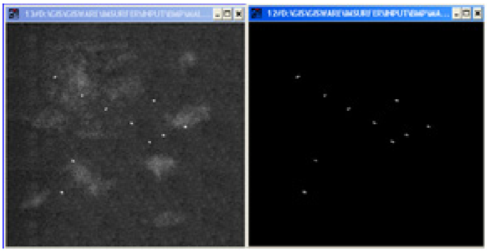

Fig. 2. Noise reduction – second example

In the first two examples the noise reduction was complete. However, in the last example some part of the noise remained in the extraction image (top and low right).

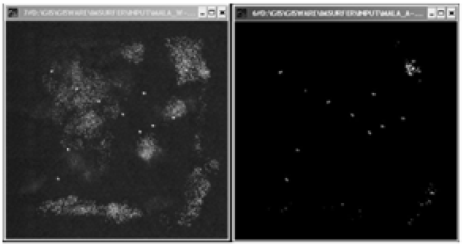

Fig. 3. Noise reduction – third example

Note that the amplitude of the target signal is lower than the chosen lower threshold in all three examples.

As we have mentioned above, described extraction procedure can be used for the extraction of heavily contaminated signals in dynamic situations provided that we have several consecutive images. The illustration example starts with the following two images (Fig.4):

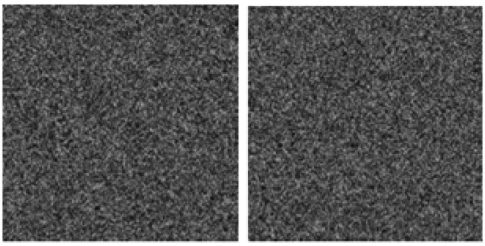

Fig. 4. Noise reduction from two images – the initial setting

After the application of the extraction procedure, we have obtained the left image on Figure 5.

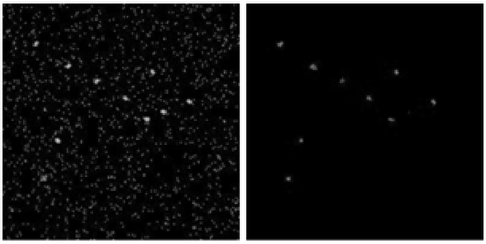

Fig. 5. Noise reduction from two images – intermediate and final stage

Note that some residual noise is present on the left image. However, after the application of the noise reduction procedure of that image, the noise reduction was complete, as it is shown on the right-side image on Figure 5.

3 Feature Extraction Based on Kalman Filters

Another method for the detection/extraction of small features is based on a so called bank of Kalman filters. After the construction of the initial sequence of images, Z_k, the bank of one-dimensional simplified Kalman filters (see [18]) is defined as follows:

$$K_k(x,y) = \frac{P_{k-1}(x,y)+Q}{P_{k-1}(x,y)+Q+R},$$

$$\hat{X}_k(x,y) = \hat{X}_{k-1}(x,y) + K_k(x,y) \cdot \left(Z_k(x,y) - \hat{X}_{k-1}(x,y)\right),$$
$$P_k(x,y) = (1 - K_k(x,y)) \cdot (P_{k-1}(x,y) + Q).$$

Initially, $P_0(x,y) = \hat{X}_0(x,y) = 0, Q = 1, R = 100$, where Q is the covariance of the noise in the target signal and R is the covariance of the noise of the measurement. Depending on the dynamics of the problem we put: the output filtered image in kth iteration is the matrix $\hat{X}_k$, the last of which is input in the procedure described by equations (1) to (7), finally generating the image with the extracted objects.

This method shows that it is not necessary to know the signal level if we can estimate the statistical parameters of noise and statistics of measured signal to some extent. In the general case, we know that its mean is somewhere between 0 and 255 and that it is contaminated with noise with the unknown variance.

The method of small object recognition, originally developed for the marine radar object tracking, works with vectors equally well. It is applicable to the automatic extraction of signals which are embedded in the noise and imperceptible (also in the spectra) in the case when we can provide at least two sources which are sufficiently linearly independent (their linear dependence on the signal components is essential for the object filtering – extraction), or in the situations when the conditions for application of Kalman filters are met.

As an illustration of the application of Kalman filters in the feature extraction, we have constructed the initial sequence of images, Z_k, of the size 200×200 pixels in the following way (Figure 6):

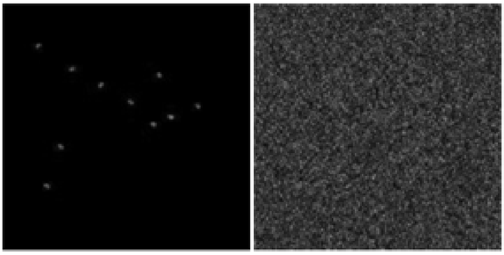

Fig. 6. Construction of Kalman filters

First, in each image we have introduced noise by $Z_k(x, y) = \mathrm{randn}(0{,}90)$, where "randn" function generates pseudo-random numbers in the interval $[0{,}255]$ using Gaussian distribution with $\mu = 0$ and $\sigma = 90$. Then, in every image we injected 10 objects (useful signals) at the same positions, each of them of a size around 10 pixels, with random (Gaussian) fluctuation of intensity around value 120 (Figure 6). After the construction of the initial sequence of images, the bank of $200 \times 200 = 40000$ one-dimensional simplified Kalman filters is defined using the iterative procedure as above. The process of noise elimination and feature extraction is shown in the images in Figure 7:

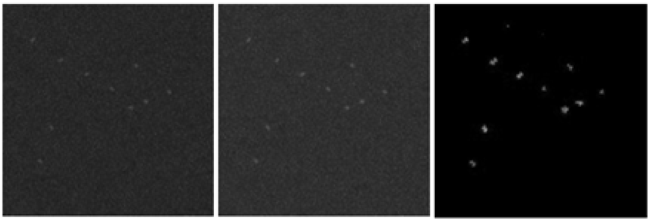

Fig. 7. Application of Kalman filters

The image on the left in Figure 7 shows the extraction result after the 21 iterations of Kalman filter bank, the central image shows the result after the 34 iterations, and the final image shows the result after 36 iterations.

4 Conclusion

This paper contains a short overview of the portion of our previous work on the problem of the automatized recognition of features in signals and their Fourier or wavelet spectra and spectrograms, see [1-8]. The algorithms sketched here use techniques developed for image processing and are suitable for morphologic investigations. These algorithms also offer possibility of localization and extraction of important features, as well as determination of their topological and geometrical characteristic invariants. Those invariants are often crucial for the representation and to classification the by application of subtle similarity measures. Small object recognition in cases of heavy contamination by noise of mainly random nature is successfully performed in rather general circumstances. Due to a modest complexity, all are real time applicable, even without the enhanced hardware.

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