SUBOPTIMAL PROCEDURE FOR SHIFTING IMAGE DETECTION IN COMPLEX SCENES

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The paper considers a suboptimal by maximum a posteriori probability criterion procedure for finding of patterns moving relative to semifixed background in the series of two staggered in time frames of slightly-varying scenes. The procedure is synthesised on the assumption that an images being analysed contains unknoun distortion and additive noise.

The procedure is based on optimum linear filtering of divergance field of previously combined by correlation method fragments of frames as well as statistical hypothesis partitioning operation applied to filter output.

The adopted statistical image model is used for development of methods for defining the main statistical characteristics for the simple detection case. The attainable value of total error is presented which arise when the synthesised procedure is applied to some characteristic scenes.

The ability to work for the procedure was proved during simulation.

KEY WORDS: Algorithm, Change Detection, Image Processing, Classification

INTRODUCTION

There is well-known (Ширман, 1986) optimum by maximum a posteriori probability criterion procedure for shifting image detection in complex scenes. The procedure is based on time-spatial filtering of the series of staggered in time frames of scenes are formed by any sensor. The procedure is highly tradious and is not practicable now. Also there are some heuristic methods (Lo, 1979; Holben 1980; Stuller, 1983; Koskol, 1986) solving this task by passing to separate time filtering and spatial filtering. All this methods use frame subtraction as the simplest form of time filtering. The main difference of this procedures is compensation of geometrical distortion on analised image are called by interframe sensor position changing.

For interframe displacements compensation the first frame is offered to be corrected by a previous researcher (Holben, 1980). The correction is described by a polinom of the second order with parameters estimated by χ^2 - criterion. The correction may be applied with the extrapolation not executed in any cases.

Another procedure was suggested in previous paper (Lo, 1979). This procedure is free from shortcomings of (Holben, 1980) and is not so tradious. In accordance with paper (Lo, 1979) the image is divided into separate fragments. The fragments are correlatively combined and for each pair divergence fields are created and then they are analysed.

Unfortunately the divergence image analysis was not given one's attention in previous papers. The attainable values of alpha and beta errors are lack of too.

The aim of this artical is the definition of mantional characters for the simplest interframe detector dealing with ideas of paper (Lo, 1979) and using linear filtering of divergance field.

1. IMAGE AND MOTION MODELS

We accume that the images available for processing consists of a discrete homogeneous random fields denoted as ι_o and ι_b in pattern and background areas and additional Gaussian noise denoted as η with exponential correlation function and average which is equal to zero. Then pixel intensity is:

$$o_i(\bar{A}) = \begin{cases} \iota_{o_i}(\bar{A}) + \eta(\bar{A}) \Leftrightarrow \bar{A} \in UT_i \subset F_i \\ \iota_{b_i}(\bar{A}) + \eta(\bar{A}) \Leftrightarrow \bar{A} \in F_i \setminus UT_i \end{cases}$$

Here $\bar{A}$ denotes the pixel coordinates vector, T_i denotes the moving object pattern area on i-th frame denoted as F_i.

With accordance to paper (Левшин, 1978) we assume that one-variable probability density functions of background $P_b(x,\bar{A})$ and pattern $P_o(x,\bar{A})$ are Gaussian:

$$\begin{aligned} &P_b(x,\bar{A}) = N(a_b,\sigma_b^2) \\ &P_o(x,\bar{A}) = N(a_o,\sigma_o^2) \\ &a_o > a_b \\ &\sigma_o \neq \sigma_b \end{aligned} \quad (1.1)$$

and their correlation functions are double exponential:

$$R\{\iota_o(\bar{\Delta})\} = \sigma_o^2 \cdot exp[-(\bar{r}_o,\bar{\Delta})]$$

$$
\begin{aligned}
&R\{\iota_b(\bar{\Lambda})\} = \sigma_b^2 \cdot exp[-(\bar{r}_b,\bar{\Lambda})] \\
&\bar{\Lambda} = (\Lambda_x,\Lambda_y)' \\
&\bar{r}_o = (r_{ox},r_{oy})' \qquad\qquad (1.2) \\
&\bar{r}_b = (r_{bx},r_{by})' \\
&r_{ox} \neq r_{oy} \neq r_{bx} \neq r_{by} \ .
\end{aligned}
$$

Let us suppose that for the time distance denoted as τ moving object pattern is displaced to $L<L_c$ value. Here L_c is a characteristic pattern size. Four peculiar regions can be distinguished in the frame difference field:

$$
\begin{aligned}
&A: \bar{A} \in F/T\big|_{t=t_1} \wedge \bar{A} \in T\big|_{t=t_2} \\
&B: \bar{A} \in T\big|_{t=t_1} \wedge \bar{A} \in F/T\big|_{t=t_2} \qquad (1.3) \\
&C: \bar{A} \in F/T\big|_{t=t_1} \wedge \bar{A} \in F/T\big|_{t=t_2} \\
&D: \bar{A} \in T\big|_{t=t_1} \wedge \bar{A} \in T\big|_{t=t_2}
\end{aligned}
$$

These definitions are illustrated by Fig.1 in which pattern position at moment t_1 is shown by dotted lines and at moment t_2 by unbroken lines.

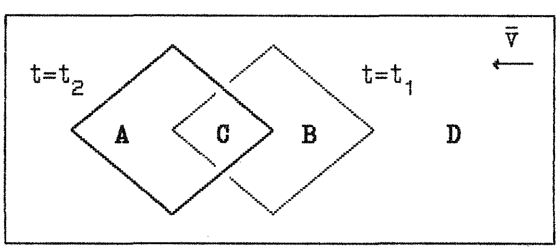

Fig.1 Peculiar regions of the frame difference field. Pattern position at moment t_1 is shown by dotted lines and at moment t_2 by unbroken lines.

We assume that frame fragment size is sufficiently small in order to

$$\forall\ \bar{A} \in F\backslash T \Rightarrow \bar{D}(\bar{A}) = \bar{D}$$

and pattern displacement has the determinate value and an accidental direction. That is

$$\forall\ \bar{A} \in T_1 \Rightarrow \bar{L}(\bar{A}) = \bar{L}\ .$$

Then with accordance to paper (Левин, 1989) we can confirm that all ragions of frame difference field are also homogeneous Gaussian. Their averages may be easily defined by Eq.(1.1)-Eq.(1.3).

2. SUBOPTIMAL DETECTOR STRUCTURE

Let's put restrictions to suboptimal detector structure. For this purporse we assume that the moving object pattern is in the middle of first frame fragment if it is present there. Then let's reduce frame quantity to two and substitute time-spatial filtering for separate time one and spatial filtering. Let's also suppoused that the spatial filter is linear one and it's area of definition is restricted to pattern size.

We shall simply assert without proof that the best result is reached for this task if time distance

$$\tau = L_c \cdot V^{-1} \qquad (2.1)$$

and fragment size

$$G = 3 \cdot L_c \ . \qquad (2.2)$$

Here V is design speed of pattern moving.

It can be shown too that for the case of simple detection (Вайнштейн, 1960) with above restrictions optimum detector of non-point moving objects has to make following operations:

(1) Frame difference field forming.
(2) Frame difference field filtering by ripple mask (Pratt, 1978) with restricted to pattern size area of definition and constant impuls response.
(3) Extremal pixels at the filter output

$$\bar{x} = (o^h_{min}, o^h_{max})'$$

searching.
(4) Decision function denoted as

$$\mathcal{G}_{ij}(\bar{x}) \Rightarrow H_{ij}$$

calculating for hypothesises

$$H_{ij}:\ o^h_{min}(\bar{A}) \Rightarrow \bar{A} \in i \wedge o^h_{max}(\bar{A}) \Rightarrow \bar{A} \in j\ .$$

Here $i,j \in \{A,B,C,D\}$.
(5) Searched pixels classification.

It's clear that moving object pattern is detected if

$$\mathcal{G}_{CC}(\bar{x}) = min\{\mathcal{G}_{ij}(\bar{x})\}\ .$$

Let's define the based on operations (1)-(5) detector as suboptimal.

3. ANALYSIS OF THE SUBOPTIMAL DETECTOR

As it was stated above frame difference image consists of a discrete homogeneous Gaussian fields. Therefore hypothesis H_{ij} a posteriori probability subjects double Gaussian distribution law. Then

$$\mathcal{G}_{ij}(\bar{x}) = \bar{x}' \cdot \theta_{ij} \cdot \bar{x} + \bar{w}'_{ij} \cdot \bar{x} + v_{ij} \qquad (3.1)$$

and separating surfaces which are associated as show Eq.(3.1) and Eq.(3.2)

$$\mathcal{G}_{CC}(\bar{x}) = \mathcal{G}_{ij}(\bar{x}) \qquad (3.2)$$

are the hyperquadrics (Duda, 1973).

In Eq.(3.1):

$$\theta_{ij} = -0.5 \cdot \Sigma^{-1}_{ij}$$

$$\bar{w}_{ij} = \Sigma_{ij}^{-1}\cdot\bar{\mu}_{ij} \qquad (3.3)$$
$$v_{ij} = -0.5\cdot\bar{\mu}'_{ij}\cdot\Sigma_{ij}^{-1}\cdot\bar{\mu}_{ij} - 0.5\cdot log|\Sigma_{ij}| + log(W_{ij})$$
$$i \neq C \wedge j \neq C .$$

Here Σ_{ij} denotes extremal pixels correlation matrix. $\bar{\mu}_{ij}$ denotes i and j regions average and W_{ij} denotes H_{ij} a priory probability.

Let's find H_{cc} region.

Filter impuls response and frame difference fild parametrs allows to define easily Σ_{ij} and $\bar{\mu}_{ij}$ (Левин, 1989). Fig. 1 shell be used for W_{ij} defining. Apriory probabilities of any pixel belonging to one of the regions followed Fig.1 are:

$$W_{AA} = W_{AB} = W_{BB} = W_{BA} = [W_1(1-W_2)]^2$$
$$W_{AC} = W_{BC} = W_{CA} = W_{CB} = W_1W_2[1-W_1(2-W_2)]$$
$$W_{AD} = W_{BD} = W_{DA} = W_{DB} = W_1^2W_2(1-W_2)^2$$
$$W_{CC} = [1-W_1(2-W_2)]^2$$
$$W_{CD} = W_{DC} = W_1W_2[1-W_1(2-W_2)]$$
$$W_{DD} = (W_1W_2)^2$$

Here moving object pattern area is W_1 about frame area and pattern has not moved to W_2 about his area for time distance τ.

We supposed in what follows that W_2=0. In this case it's easy to make sure (see (Левин, 1989)) that regions in which hypothesises are true are placed as it shown in Fig.2.

As it follows from Eq.(3.1), Eq.(3.2) and Eq.(3.3) hyperquadrics is defined by hypothesises parameters and may have different forms in some cases. In Fig.2. we show the simplest case in which random filds are not correlated.

It's easy to make sure that with above restrictions total error of detector is:

$$\alpha = \sum_{\substack{i\neq C \\ j\neq C}} W_{ij}\cdot P_{ij}(\bar{x}|\bar{x}\in\Omega_{CC})$$
$$\beta = W_{CC}\cdot P_{CC}(\bar{x}|\bar{x}\notin\Omega_{CC})$$
$$P_{\Sigma} = \alpha + \beta ,$$

where Ω_{CC} is hypothesis H_{CC} acceptence region.

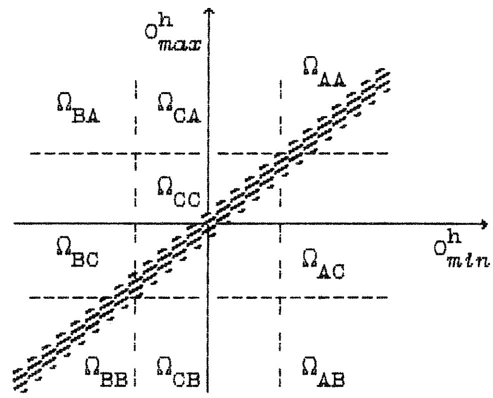

Fig.2 Hypothesises acceptence regions. Admissible hypothesises are above heavy line.

As $\sigma^h_{min} \leqslant \sigma^h_{max}$ admissible hypothesises are above heavy line in Fig.2. Then H_{AB}, H_{AC} and H_{CB} hypothesises are not admissible. This makes some easily total error calculating. Nevertheless it remains very tradious.

As previous resercher (Holben, 1980) we have examined some particular cases which are typical for airborne sensors. Examined range of the pattern and background parameters is shown in table 1.

Table 1. Range of examined parameters

Parameters	Field type		
	Background	Pattern	Noise
Average	0.240-0.400	0.320-0.550	0.000
Standart deviation	0.036-0.265	0.042-0.200	0.0I4-0.044
Correlation constant	0.523-2.0I3	I.043-5.996	25.56-3I.I2

Here average and standart deviation is defined about maximum pixel value. Correlation constant is defined about characteristic pattern size.

The dependence of the total error on the background displacement for typical scene in some seasons is shown in Fig.3. We supposed that W_1=0.001.

In Fig.3 displacement value is defined about characteristic pattern size.

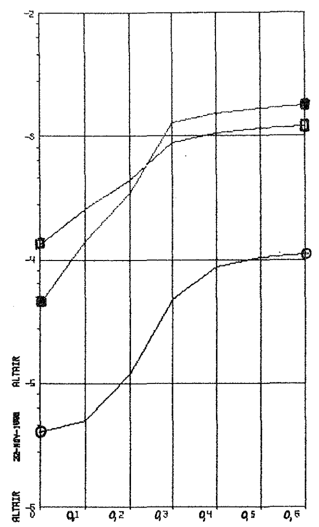

Fig.3 Dependence of the total error on the backgrownd displacement for the typical scene in diferent seasons. Winter is marked by ⊙, autumn - by ■ and summer - by □.

maximum increases the total error in 7 - 20 times.

4. PROCESSING ILLUSTRATION

Let's illustrate the ability to work of the suboptimal detector after the example of experimental-based frames digital processing.

In Fig.4 you can see the first frame. We used this frame above for detector analisis. The frame parameters are equal to: a_o=38.1 a_b=25.2 σ_o=6.2 σ_b=5.7 r_{ox}=.874 r_{oy}=3.469 r_{bx}=.040 r_{by}=.183.

The histogramm of intensity and correlative function of this frame landscape IR-image is shown in Fig.5 by broken lines.

As shown in Fig.5 the histogramm of intensity is well approcsimated by Gaussian curve and correlation function by exponential curve. It's shown in Fig.5 by smoose lines.

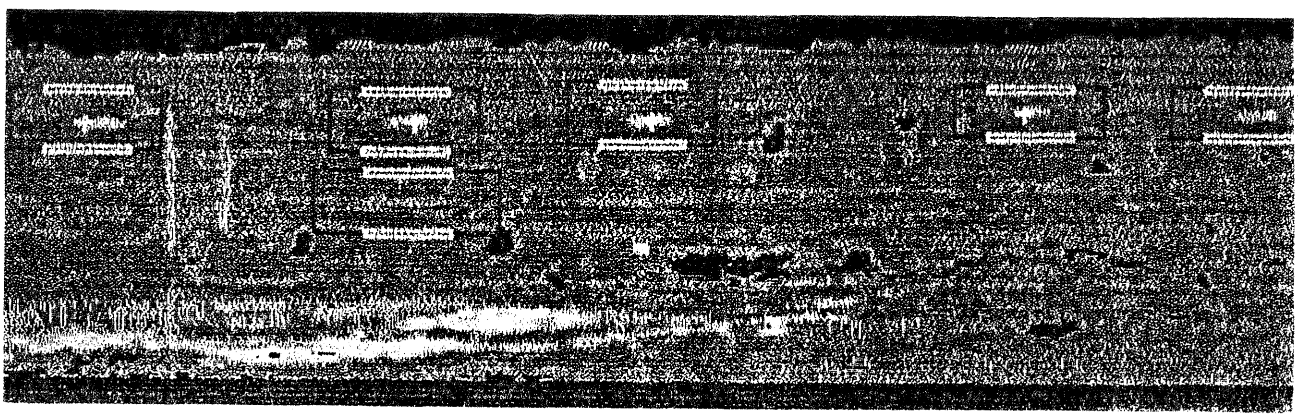

Fig.4 Experimental image. The first frame. Processing fragments is bordered by black lines. Correlation processing area is drawn by white lines.

We shall suppose in what follows that interframe processing is well founded if total error of suboptimal detector is less then singlframe one. Linear singlframe detector of bright area was described in paper (Вайнштейн, 1960). The total error is shown in table 2 for this detector.

The first frame has been processing by optimum linear pattern detector which was described in paper (Вайнштейн,1960). As a result six regions have been picked out. Five of them corresponds to the moving object patterns. The fagments have been segmented round the all region centre. You can see these fragments in Fig.4 (it was drawn by black lines). Fragment size has been choosen in accordance with Eq.(2.2).

Table 2. Singlframe detector errors for some seasons

Features	Season		
	Winter	Autumn	Summer
Total error	$0.932\cdot10^{-4}$	$0.747\cdot10^{-3}$	$0.961\cdot10^{-3}$

The results followed table 2 and Fig.3 are:

(1) The overframe processing is well founded for $|D|\leqslant(0.2 - 0.4)L_c$.

(2) The changing of the background interframe displasement from zero to

By the moment of the second frame forming which was determined according to

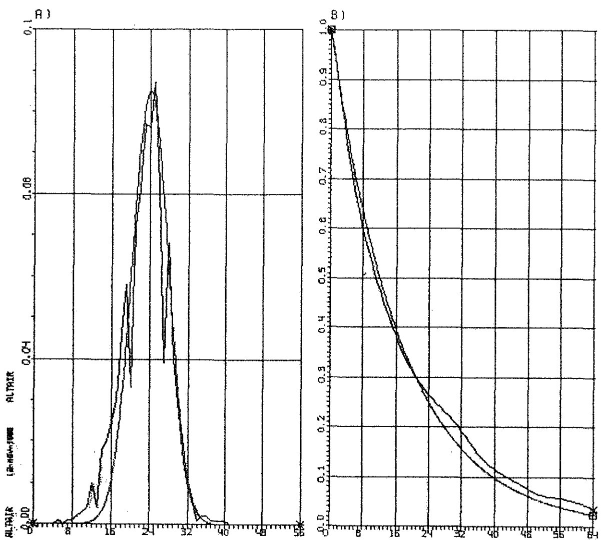

Fig.5 Approcsimation of the histogramm of intensity (Fig.5a) and correlative function (Fig.5b) of a typical landscape. Broken lines is experimental and smooth lines is approcsimated curves.

Eq.(2.1) the distance along the line of sight has been decreased by 7% along the frame border - by 23% and along the distant border - by 1% approximately.

Here W_1=0.2.

Enlarged by three times approximately frame difference fields of processing fragments are shown in Fig.6. Before the subtraction the fragments have been preliminaryly combined in accordance with the serial correlation algorithm (Barnea, 1972). Correlation processing areas are drawn by white lines in Fig.4. In Fig.6 the fragment interframe displacement is one pixel along Y datum line and two pixels along X one.

You can see in Fig.6 that the real speed of moving pattern is less than design one which causes partial pattern shading.

Fragment frame difference fields have been filtered by trunckated to pattern area constant impuls response filter. We use extremal filter outputs to decision function calculation. Decision function values for each fragments are shown in table 3.

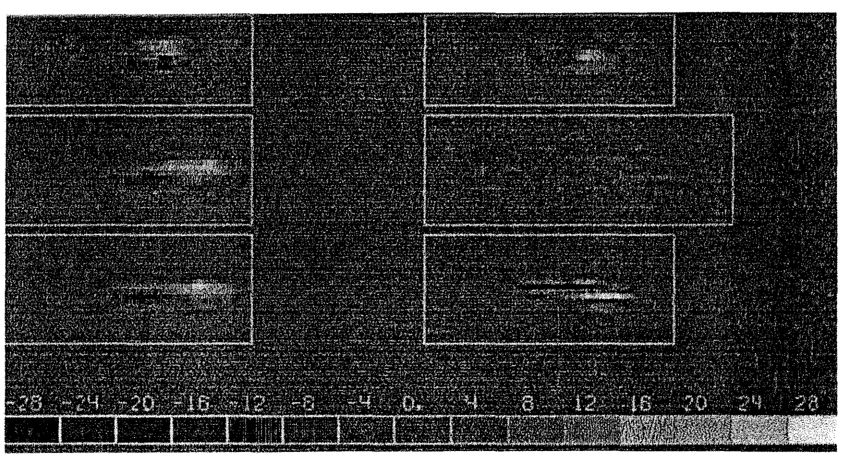

Fig.6 The result of preliminary combined fragments subtraction.

Table 3. Extremal filter outputs and decision function values

Features	Fragment number					
	I	2	3	4	5	6
O^h_{min}	-3.8	-1.9	-6.1	0.6	-4.5	-2.7
O^h_{max}	5.9	6.0	8.9	1.7	7.6	4.7
$P_{AA}(\bar{x})$	.00001	.00012	.00000	.00032	.00001	.00001
$P_{BB}(\bar{x})$	.00000	.00001	.00000	.00001	.00000	.00000
$P_{CC}(\bar{x})$	.00004	.00009	.00000	**.03250**	.00002	.00012
$P_{BA}(\bar{x})$	**.00379**	.00036	**.02089**	.00015	**.00868**	**.00063**
$P_{BC}(\bar{x})$	.00004	.00000	.00014	.00006	.00003	.00003
$P_{CA}(\bar{x})$	.00283	**.00814**	.00037	.00251	.00064	.00121

As it shown in table 3 the fragments numb.1, 3, 5, 6 decision function value are maximum for H_{BA} hypothesis. Decision function value for fragment numb.4 which havn't moving pattern is maximum for H_{CC} hypothesis. Fragment numb.2 one is maximum for H_{CA} hypothesis. This is consequence of partial pattern shading.

Thus propoused suboptimal procedure makes absolute true result.

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