ON ADAPTIVE PATTERN SELECTION FOR BLOCK MOTION ESTIMATION ALGORITHMS

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ABSTRACT

Pattern-based block motion estimation (PBME) algorithm has been widely adopted in digital video coding systems. Due to the large characteristics variations among video sequences, adaptive PBME algorithms that switch search patterns have been proposed. However, most adaptive search algorithms are heuristically designed based on the experimental data. In this paper, we like to construct an analytical model and explore the problem systematically. Also, we propose an adaptive genetic pattern search algorithm (AGPS). Simulations show that the proposed AGPS in average outperforms the existing popular search algorithms quite significantly in speed, while the peak signal noise ration (PSNR) quality is maintained at the same level.

Index Terms— adaptive pattern selection, genetic algorithm, pattern based block motion estimation, motion estimation, video compression.

1. INTRODUCTION

Block-based motion estimation (BME) has been a very popular tool in the modern video coding systems. According to [1], fast BME algorithms can be classified into two main categories, namely, reduction of the number of search (checking) points, and reduction of computational complexity in calculating the block matching cost for each search point. This paper focuses on the algorithms in the first category.

To reduce the number of checking points, a BME algorithm typically use the following techniques: 1) an operative threshold for terminating the search process [2], 2) the selection of proper starting points by using various predictors [3], and 3) an effective set of search patterns [2][4][5]. With the help of these techniques, recent BME algorithms can effectively reduce computation and keep the desired level of quality. The first and second sets of techniques rely on the high correlation of data among intra or inter frames. And the third techniques (search patterns) work on the fact that the matching-cost surface is nearly monotonic. Among these techniques, the search patterns have a decisive influence on the performance of a search algorithm especially when the data correlation is low.

Researchers often design search patterns intuitively based the experimental motion vector (MV) data. But, because the characteristic of an image sequence varies quite drastically along the time axis, one single search pattern often cannot match the different characteristics of the entire sequence. Thus, some studies proposed adaptive pattern-based motion estimation (PBME) methods by switching search patterns to fit the video content [6]. However, most proposals are heuristic ideas developed based on empirical data. In the following paragraphs, we like to construct an analytical model and explore the problem systematically.

Based on our proposed model for PBME, we analyze the performance of various search algorithms and propose a practical threshold for search pattern selection in Section 2. Based on the analysis, we propose an adaptive genetic pattern search in Section 3. Experiment results are shown in Section 4. And conclusions are given in Section 5.

2. SELECTION OF SEARCH PATTERNS

In this section, we first construct a mathematical model of PBME to unveil the relationship between the search pattern, the video sequence, and the average number of search points. Then, we compare the performance of two popular search patterns. Based on our observations, we propose a practical threshold for adaptive selection of search patterns.

2.1. Modeling of Pattern-based Motion Estimation

$$ASP = C_1 \times \sum_{x,y \in A} S_{FS}(x,y) \times WF_{SA}(x,y) + C_2 \tag{1}$$

$$S_{FS}(x,y) = \frac{\dfrac{1}{|x|^{5/3}+\zeta_x}\,\dfrac{1}{|y|^{5/3}+\zeta_y}}{\displaystyle\sum_{(x',y')\in A} \dfrac{1}{|x'|^{5/3}+\zeta_x}\,\dfrac{1}{|y'|^{5/3}+\zeta_y}} \tag{2}$$

In [7], we present a mathematical model (1) to predict the average number of search points (ASP) produced by a PBME. This model consists two components: a statistical probability distribution function $S_{FS}(x,y)$ of MV (2), which is picture-dependent, and the minimal number of search points, $WF_{SA}(x,y)$, (called *weighting function*) produced by a search algorithm (SA). In (1), x and y are relative coordinates with respect to (w.r.t.) the predicted motion vector (PMV). And the parameters (C_1, C_2) are obtained by training methods. Note that C_1 is always positive, because ASP and the sum of products of $S_{FS}(x,y)$ and $WF_{SA}(x,y)$ are always positively correlated. In (2), (x,y) and (x',y') are relative coordinates w.r.t PMV, and A is the search area. The parameters (ζ_x, ζ_y) of $S_{FS}(x,y)$ are obtained by numerical methods such that the variances of $S_{FS}(x,y)$ match those of MVs acquired by applying the full search to a specific sequence. In other words, (ζ_x, ζ_y) are functions of MV variances.

The weighting function of a search algorithm can be obtained by analyzing the search procedure of an algorithm. In Fig. 1, the weighting functions of the well-known enhanced hexagonal search (EHS) [4] and easy rhombus pattern search (ERPS) are shown. The ERPS described here is the adaptive rood pattern search [2] without using various predictors. The value on a contour represents the minimal number of search points for a search algorithm to move from the origin to a point (location) on the contour. The weighting function is a discrete function, and the data points exist only on the integer coordinates. For the ease of visualization, the data points are interpolated to form continuous contour lines.

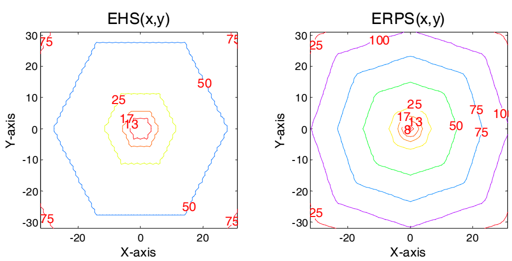

Fig. 1. The Weighting Function of EHS and ERPS.

We suggest two training methods to decide the parameters (C_1, C_2) [7]. In the first method, we apply a fixed search algorithm to a set of training sequences to compute the parameters. Therefore, we may predict the ASP of a new sequence. In the second method, the parameters are acquired by applying a set of search algorithms (training algorithms) to a specific sequence. Thus, we can predict the ASP of a new search algorithm. Method 2 is used in this paper.

2.2. Performance Comparison of Search Patterns

Using our model, when we apply two search algorithms, SA1 and SA2, to a specific sequence, the difference in ASP is shown in (3). Because WF_{SA1} and WF_{SA2} are fixed, and S_{FS} is a function of the MV variances, it is clear that D_{ASP} is a function of MV variances.

We define the *performance index* (I_{ASP}) by (4). The I_{ASP} between ERPS and EHS is shown in **Fig. 2**(a). The X-axis denotes the MV variance in the horizontal direction, and the Y-axis denotes that in the vertical direction. When $I_{ASP} > 0$, ERPS outperforms EHS in terms of ASP, and when $I_{ASP} < 0$, EHS is better. When the sequence differs, only the magnitude of C_1 varies, not the sign. Consequently, it is easy to decide which search algorithm is better, as long as the MV variances of a video sequence are known. The threshold is the variances pair at which I_{ASP} equals zero. Although this threshold, $I_{ASP}=0$, is a curve, we can use a straight line (5) to approximate (4) as shown in **Fig. 2**(a). That is, we use (5) to decide which algorithm to use, wherein P, Q, and R are determined by applying numerical methods to data.

$$D_{ASP} = C_1 \times \sum_{x,y \in A} S_{FS}(x,y) \times (WF_{SA1}(x,y) - WF_{SA2}(x,y)) \quad (3)$$

$$I_{ASP} = D_{ASP} / C_1 \quad (4)$$

$$P \cdot VAR_X + Q \cdot VAR_Y = R \quad (5)$$

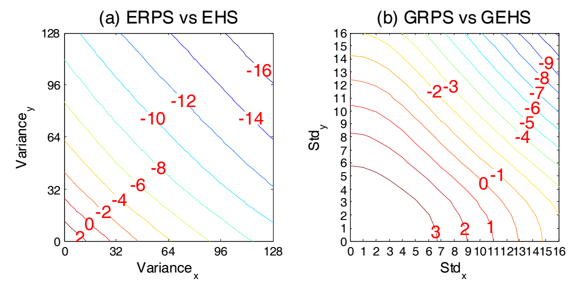

Fig. 2. The I_{ASP} between ERPS and EHS, and between GRPS and GEHS.

In addition, **Fig. 2**(a) rectifies a commonly accepted concept that small search patterns are more suitable for 'low motion sequences', while large search patterns are for 'high motion sequences'. To be exact, the small patterns are more suitable for 'low MV variance' sequences, since the ASP performance of a search algorithm is determined by the MV variances.

3. AN ADAPTIVE GENETIC PATTERN SEARCH

Adopting the threshold defined by (5), we propose an adaptive genetic pattern search algorithm (AGPS), which uses two search pattern sets, the genetic rhombus search patterns (GRPS) and the genetic enhanced hexagonal search patterns (GEHS).

The flow chart of GRPS is shown in Fig. 3 and its search patterns are shown in Fig. 5. In step 2 (S2), it checks one of the search points in Fig. 5(a), and in step 3B (S3B), it examines if all the points in Fig. 5(b) have been checked. The flow chart of GEHS is shown in Fig. 4 and its associated search patterns are shown in Fig. 6. In step 2 (S2), it checks one of the search points in Fig. 6(a). In step 3B (S3B), it examines if all the points in Fig. 6(b) are checked. In step 4 (S4), six block matching costs are computed using the two–point patterns in the hexagonal pattern as indicated by Groups I to VI in Fig. 6(b). Then, determine which search pattern (direction) to be used next. When the smallest cost is in Groups II, III, V, and VI in Fig. 6(b), two extra points are checked, as exemplified in Fig. 6 (c). Or, if the smallest cost is in Groups I and IV in Fig. 6(b), three extra points are checked, as exemplified in Fig. 6(d).

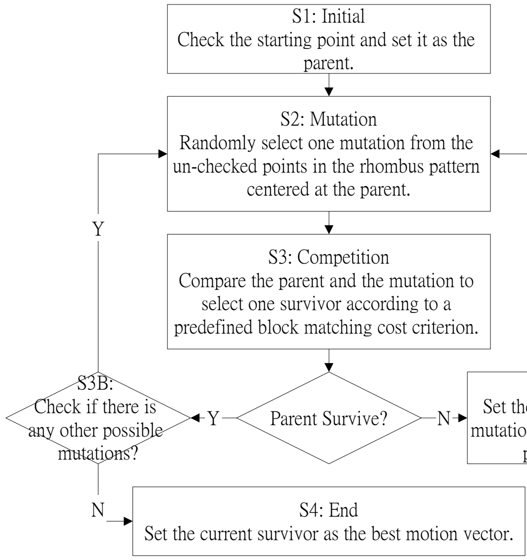

Fig. 3 Flow chart of GRPS

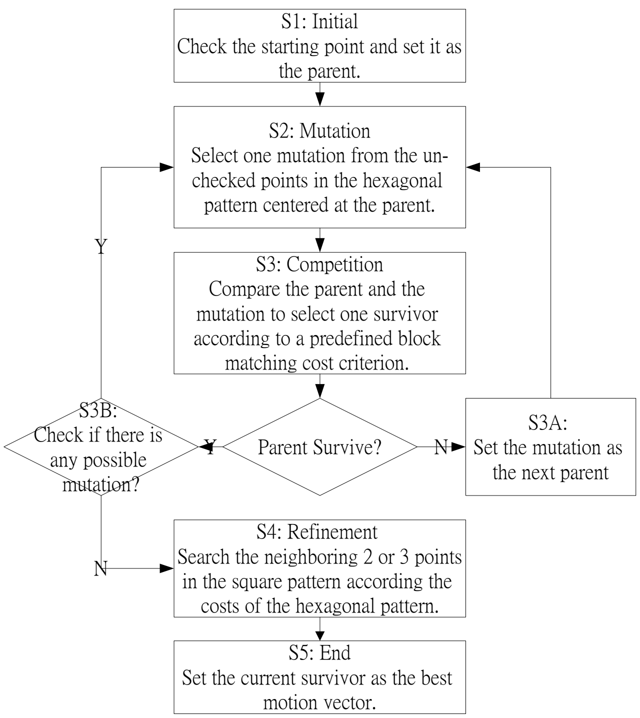

Fig. 4 Flow chart of GEHS

As shown in **Fig. 7**, the weighting functions of GRPS and GEHS are smaller than those of ERPS and EHS in **Fig. 1**, respectively. Thus, we adopt GRPS and GEHS as our search patterns. Combining GRPS and GEHS, the flow chart of AGPS is shown in Fig. 8. Herein, the standard deviations of MV are obtained from the MVs in the previous frame. And the threshold can be thus determined by examining the I_{ASP} diagram in Fig. 2(b). We use standard deviation instead of variance, because I_{ASP}=0 curve in Fig. 2(b) is better approximated by a straight line in the standard deviation domain. Thus, (5) is modified to (6). We choose A=B=1 and TH=12 in our simulations.

$$A \cdot STD_X + B \cdot STD_Y = TH \tag{6}$$

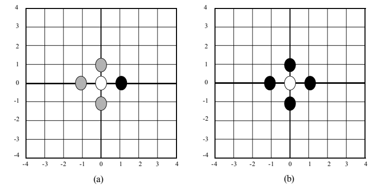

Fig. 5 Search patterns of GRPS

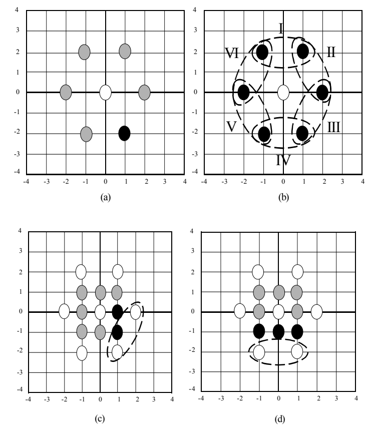

Fig. 6 Search Patterns of GEHS

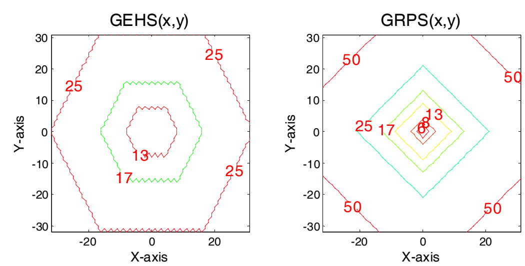

Fig. 7 The Weighting Function of GEHS and GRPS

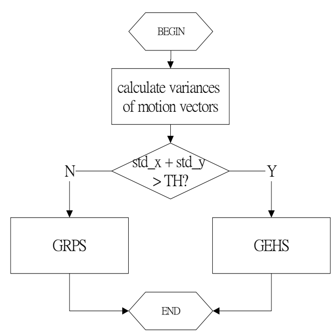

Fig. 8 Flow Chart of AGPS

4. EXPERIMENTAL RESULTS

To test the proposed algorithm, four sequences with different MV variances (denoted as '1X') are tested under the setting given in Table I. To test the extreme cases, we generate four new test sequences consisting of the odd frames of these sequences (denoted as '2X'). They equal to the two times fast forward of the originals. These 8 test sequences are coded by an MPEG-4 SP@L3 encoder. All the sequences are in the CIF (352X288) format. Only the first frame is coded as I frame, and all the remaining frames are coded as P frame. The search range is 16, and the block size is 16x16.

Table I. Test Sequences and Their Settings

Abbreviation	Sequence	Bitrate (K bps)	Frame rate (fps)	Number of frames
md96	mother and daughter	96	10	300
fm512	foreman	512	30	300
fb1024	football	1024	30	90
st1024	steven	1024	30	300

Table II. ASP (Average Number of Search Points)

Type	ASP	AGPS	ERPS	EHS	DS	FS
1X	md96	5.98	6.83	10.32	14.85	1024
	fm512	7.13	8.65	10.76	16.17	1024
	fb1024	11.58	16.36	14.29	22.36	1024
	st1024	7.65	9.95	11.48	16.96	1024
2X	md96	6.4	7.56	10.66	15.44	1024
	fm512	8.81	11.70	12.21	18.72	1024
	fb1024	14.76	22.32	17.29	27.39	1024
	st1024	9.28	12.45	13.07	19.49	1024
	Average	8.95	11.98	12.51	18.92	1024

Table III. PSNR (Peak Signal Noise Ratio)

Type	PSNR	AGPS	ERPS	EHS	DS	FS
1X	md96	40.06	40.09	39.87	39.99	39.80
	fm512	34.05	34.10	33.94	34.06	34.06
	fb1024	34.79	34.88	34.86	34.93	35.28
	st1024	29.39	29.31	29.47	29.44	29.48
2X	md96	38.661	38.66	38.43	38.60	38.41
	fm512	32.333	32.45	32.21	32.38	32.42
	fb1024	33.216	33.24	33.25	33.28	33.44
	st1024	27.988	27.93	27.96	27.97	28.10
	Average	33.81	33.83	33.75	33.83	33.87

Table IV. Performance Comparison

	Gain	AGPS Over ERPS		AGPS Over EHS		AGPS over DS		AGPS over FS	
Type	Sequence	CG	QG	CG	QG	CG	QG	CG	QG
1X	md96	14%	-0.03	73%	0.19	148%	0.07	170.24	0.26
	fm512	21%	-0.05	51%	0.12	127%	-0.01	142.62	0.00
	fb1024	41%	-0.09	23%	-0.07	93%	-0.14	87.43	-0.49
	st1024	30%	0.08	50%	-0.07	122%	-0.05	132.86	-0.09
2X	md96	18%	0.00	67%	0.23	141%	0.06	159.00	0.25
	fm512	33%	-0.12	39%	0.12	112%	-0.05	115.23	-0.09
	fb1024	51%	-0.02	17%	-0.03	86%	-0.06	68.38	-0.22
	st1024	34%	0.06	41%	0.03	110%	0.02	109.34	-0.11
	Average	30%	-0.02	45%	0.06	117%	-0.02	123.14	-0.06

The average number of search points (ASP) and peak signal noise ratio (PSNR) for various sequences and search algorithms are listed in **Table II** and **Table III**, respectively. And a pair-wise performance comparison is given in **Table IV**. In **Table IV**, the computing gain (CG) is defined as the ratio of ASP minus one, and the quality gain (QG) is the PSNR difference. In summary, the ASP of AGPS on the average is 30% faster than that of ERPS, 45% faster than EHS, 117% faster than DS (diamond search) and 123 times faster than FS (full search). And the PSNR of AGPS is about the same as that of all the other search algorithms (+0.06dB~-0.06dB).

Run time profiling shows that the overhead in calculating the MV variances once per frame consumes around 2% computing time in the proposed algorithm. Such overhead is quite marginal. Moreover, **Table V** shows the frequency of using GRPS and GHPS in AGPS. For a typical sequence, the ME process is dominated by GRPS. But GEHS helps for high MV variance sequences.

Table V. Frequency of GRPS and GEHS

Type	1X		2X	
Ratio	GRPS	GEHS	GRPS	GEHS
md96	100%	0%	100%	0%
fm512	100%	0%	93%	7%
fb1024	70%	30%	45%	55%
st1024	100%	0%	100%	0%

5. CONCLUSIONS

This paper proposes a systematic approach to analyze the adaptive PBME problem. Based on our previously proposed PBME model, we design an adaptive genetic pattern search (AGPS) scheme which combines GRPS and GEHS. Using the standard deviation of MVs in the previous frame to decide which search algorithm to be used in the current frame, the proposed algorithm achieves more than 30% acceleration in terms of the average search points while it maintains a similar level of picture quality.

6. References

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