Transactions Letters

The Gray Prediction Search Algorithm for Block Motion Estimation

Jer Min Jou, Pei-Yin Chen, and Jian-Ming Sun

***Abstract*—Due to the temporal and spatial correlation of the image sequence, the motion vector of a block is highly related to the motion vectors of its adjacent blocks in the same image frame. If we can obtain useful and enough information from the adjacent motion vectors, the total number of search points used to find the motion vector of the block may be reduced significantly. Using that idea, an efficient gray prediction search (GPS) algorithm for block motion estimation is proposed in this paper. Based on the gray system theory, the GPS can determine the motion vectors of image blocks quickly and correctly. The experimental results show that the proposed algorithm performs better than other search algorithms, such as 3SS, CS, PHODS, 4SS, BBGDS, SES, and PSA, in terms of six different measures: 1) average mean square error per pixel; 2) average peak signal-to-noise ratio; 3) average prediction errors per pixel; 4) average entropy of prediction errors; 5) average percentage of unpredictable pels per frame; and 6) average search points per block.**

***Index Terms*—Block matching algorithm, gray prediction, motion estimation, motion vector, temporal redundancy.**

I. Introduction

The motion estimation/compensation techniques are efficient methods to reduce the required bit rate by eliminating temporal redundancy of the image sequence. The most popular technique for motion estimation is the block matching algorithm (BMA). In a typical BMA, a frame is divided into nonoverlapped square blocks of $N \times N$ pels. Then for a maximum motion displacement of W pels per frame, the current block of pels is matched against a corresponding block at the same coordinate but in the previous frame, within the square search area of width $N+2W$. A straightforward BMA is the full search algorithm (FS), which exhaustively searches for the best matched block within the search area to get the optimal motion vector. Since the total number of search points used to find the motion vector of each block is $(2W+1)^2$ for FS, with its operation speed it is not easy to meet the requirement of real-time applications. Thus, efficient search algorithms such as the three-step search algorithm (3SS) [1], cross-search algorithm (CS) [2], parallel hierarchical one-dimensional search algorithm (PHODS) [3], four-step search algorithm (4SS) [4], block-based gradient descent search algorithm (BBGDS) [5], and simple and efficient search algorithm (SES) [6] have been developed to reduce the computational complexity.

Due to the temporal and spatial correlation of the image sequence, the motion vector of a block is highly related to the motion vectors of its adjacent blocks in the same image frame. If we can obtain useful and enough information from the adjacent motion vectors, the total number of search points used to find the motion vector of the block may be reduced significantly. Based on this idea, the fast stochastic block matching algorithm (SBMA) [7] and the prediction search algorithm (PSA) [8] are proposed. In fact, the real relation among the adjacent motion vectors is neither deterministic (white) nor totally unknown (black) but is partially known (gray). This characteristic is very similar to that of a gray system. Hence, gray system theory [9] is well suited for analyzing and predicting the behavior of motion vectors.

We present a gray prediction search (GPS) algorithm for block motion estimation in this paper. Based on the gray system theory, the motion vectors of the adjacent blocks in the current frame are used to find the predicted motion vector of the current block. Using the predicted vector, the GPS can determine the initial center of the search area for the current block. Then, the GPS searches the whole search area with a 3×3 movable search window until the local minimum point lies in the center of the present search window or the number of iterations of the search loop reaches the given maximum. Since the GPS starts searching from the better initial search center, it can determine the motion vectors of image blocks more correctly and quickly, as demonstrated in Section III.

II. The Proposed Algorithm

A. Overview of Gray System Theory

The gray theory, applicable to the prediction problem of a time-varying nonlinear system, was first proposed by Deng in 1982 [9] and has been widely and successfully used in many fields, such as economics, geography, weather, and automatic control [10], [11]. Instead of forming a knowledge base, the gray model constructs some differential equations to characterize the controlled system behavior. By using a few past output data and solving the differential equations, the gray model can predict the future behavior of the system accurately. In this paper, a kind of single variable and first-order linear dynamic gray model, named as GM(1, 1), is adopted.

Manuscript received January 26, 1998; revised January 18, 1999. This work was supported in part by the National Science Council, R.O.C., under Grant NSC-87-2213-E-006-031. This paper was recommended by Associate Editor B. Zeng.

The authors are with the Department of Electrical Engineering, National Cheng Kung University, Tainan, Taiwan 70101 R.O.C.

Publisher Item Identifier S 1051-8215(99)07024-X.

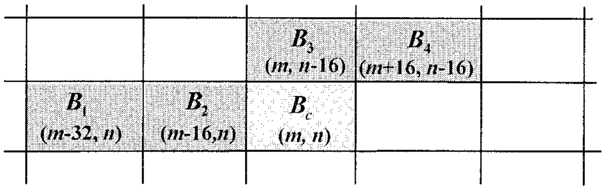

Fig. 1. The position relation of the current block and the reference blocks.

In most cases, the raw data obtained by measuring the system is lack of interrelations and is insufficient to establish a gray model. Some manipulation on the raw data is needed to get a more regular data sequence. As most gray systems do, the accumulated generating operation (AGO) is used in the design. Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ be the original data sequence, where $x^{(0)}(i)$ represents the system output at time i. The new sequence $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$ generated with the AGO is derived as follows:

$$x^{(1)}(k) = \sum_{m=1}^{k} x^{(0)}(m), \qquad k \in \{1, \ldots, n\}. \tag{1}$$

According to GM(1, 1), we can form the following first-order gray differential equation:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b.$$

By solving the differential equation, we can get the prediction function for the gray system

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a} \quad \text{for } k > 0 \tag{2}$$

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad \text{for } k > 0 \tag{3}$$

where $\hat{x}$ denotes the prediction of x and a and b are determined by

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T y_n \tag{4}$$

$$B = \begin{bmatrix} -0.5\left(x^{(1)}(1) + x^{(1)}(2)\right) & 1 \\ -0.5\left(x^{(1)}(2) + x^{(1)}(3)\right) & 1 \\ \cdots & \\ -0.5\left(x^{(1)}(n-1) + x^{(1)}(n)\right) & 1 \end{bmatrix} \tag{5}$$

$$y_n = \left[x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\right]^T. \tag{6}$$

B. Gray Prediction for Motion Vector

Since the relation among the adjacent motion vectors in an image frame is gray, the GM(1, 1) is applied to predict the motion vectors of blocks. Fig. 1 shows the position relation of the current block and the reference blocks used for gray prediction in which each block is of size 16 × 16. The current block, denoted as B_c, is located at (m, n), where $m(n)$ is the column (row) number. Its four neighboring blocks, at location $(m-32, n), (m-16, n), (m, n-16)$, and $(m+16, n-16)$, are denoted as B_i for $i \in \{1, 2, 3, 4\}$. Let the motion vector of B_i be represented by $V_i = [\Delta c_i, \Delta r_i]$, and let $\hat{P} = [\Delta \hat{c}_P, \Delta \hat{r}_P]$ mean the predicted motion vector of B_c. Then, $\Delta \hat{c}_P$ is calculated by using the following gray prediction steps.

Step 1) Construct the original data sequence

$$\begin{aligned} X^{(0)} &= \left(x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4)\right) \\ &= ((\Delta c_1 + 100), (\Delta c_2 + 100), (\Delta c_3 + 100), \\ &\quad (\Delta c_4 + 100)). \end{aligned}$$

Step 2) Generate the new data sequence $X^{(1)}$ with AGO [see (1)].

Step 3) Determine a and b using (4)–(6).

Step 4) Calculate $\hat{x}^{(0)}(2)$ and $\hat{x}^{(0)}(3)$ using (2) and (3). Then determine $\Delta \hat{c}_P$ as follows:

$$\begin{aligned} \Delta \hat{c}_P &= \frac{(\Delta \hat{c}_2 + \Delta \hat{c}_3)}{2} \\ &= \frac{\left(\left(\hat{x}^{(0)}(2) - 100\right) + \left(\hat{x}^{(0)}(3) - 100\right)\right)}{2}. \end{aligned} \tag{7}$$

To smooth the gray prediction curve, we generate the data sequence $X^{(0)}$ by adding 100 to each Δc_i. Additionally, we assume that $\Delta \hat{c}_P$ is close to the values of $\Delta \hat{c}_2$ and $\Delta \hat{c}_3$, the predicted vectors of block B_2 and B_3. Therefore, $\Delta \hat{c}_P$ is given as (7). Similarly, $\Delta \hat{r}_P$ is calculated through the same four steps by replacing Δc_i with Δr_i. Thus, the predicted motion vector $\hat{P}$ can be determined. Actually, the above prediction procedure can also be performed with only three adjacent blocks, B_1, B_2, and B_3. The different results using three and four adjacent blocks will be described in Section III.

C. Gray Prediction Search Algorithm

Suppose that the current block is located at the coordinate (m, n). Let *Count* represent the maximum iteration times of the search loop set by users and BDM mean the block distortion measure used for motion estimation. The GPS algorithm is summarized as follows.

Step 1) Utilize the gray prediction procedure described in subsection B to obtain the predicted motion vector $\hat{P} = [\Delta \hat{c}_P, \Delta \hat{r}_P]$. Then set the initial center of the search area at the coordinate $((m + \Delta \hat{c}_P), (n + \Delta \hat{r}_P))$ and the loop counter (S) to one.

Step 2) Find the minimum BDM point among the nine checking points on a 3 × 3 movable search window.

Step 3) If $S > Count$ or the minimum BDM point is located at the center of the present search window, go to Step 4); otherwise, increase S by one, perform the search process with the following two search patterns, and then repeat this step.

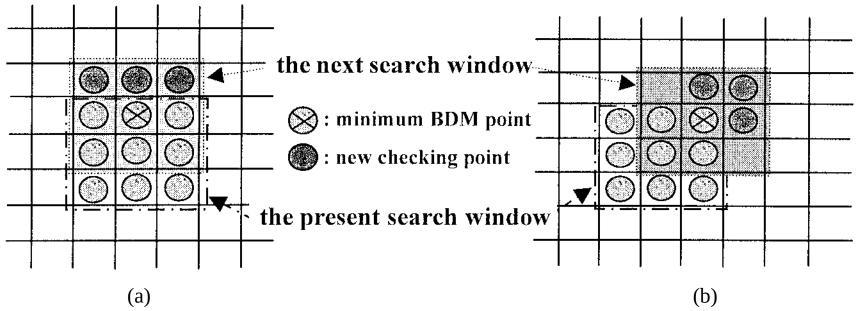

Fig. 2. Two search patterns of the GPS.

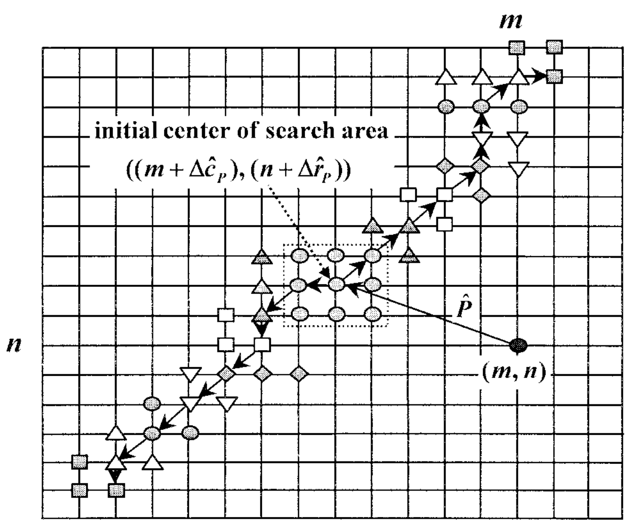

Fig. 3. Two different search paths of the GPS.

a) If the minimum BDM point is located at the middle of the boundary column (row) of the present search window, the center of the next search window is shifted to the minimum BDM point, and three additional vertical (horizontal) adjacent checking points as shown in Fig. 2(a) are used.

b) If the minimum BDM point is located at the corner of the present search window, the center of the next search window is shifted to the minimum BDM point, and three additional checking points as shown in Fig. 2(b) are used.

Step 4) Stop the search and calculate the overall (or final) motion vector.

Even if we use a 3 × 3 a movable search window, only part of the window (not all nine search points) is searched. Thus, some unnecessary search points can be omitted. With the halfway-stop technique, the GPS algorithm stops the search process as soon as the minimum BDM point is found at the center of the present search window. Two examples of GPS are shown in Fig. 3 with different search paths as $Count = 8$; for the worst case, the total number of search points required is $(9+3\times(8-1)) = 30$. However, the minimum BDM point will be found at the center of the present search window at the first or second search iteration if we can always make good prediction. Thus, the average search points can be reduced significantly. That can be proven according to the experimental results described in the following section.

III. Experimental Results and Performance Comparisons

Since the gray prediction procedure requires complex computations, the table-lookup approach is applied to reduce the implementation complexity and to prompt the prediction speed. If three adjacent motion vectors are used for gray prediction, a table with $2^{4\times 3}$ entries must be constructed, in which each entry needs four bits to store a predicted vector value between -7 and 7. Similarly, a table with $2^{4\times 4}$ entries is needed while four adjacent motion vectors are used for prediction. Thus, the two tables need 2 K and 32 K bytes of memory, respectively.

In our experiments, the BDM is defined to be the mean squared error (MSE) and the block size is fixed at 16 × 16. The maximum motion displacement is set to ± 7. The first 100 frames of the *Football, Mobile, Windmill, Flower, Tennis, Salesman,* and *Miss America* sequences (in CIF format) are used to test the proposed algorithm. It is noted that these sequences contain different combinations of still, slow, and fast moving objects. The comparisons are made by using nine search algorithms: 1) FS, 2) 3SS, 3) CS, 4) PHODS, 5) 4SS, 6) BBGDS, 7) SES, 8) PSA, and 9) GPS in terms of six different measures:

1) average MSE per pixel, as shown in Table I;
2) average peak signal-to-noise ratio (PSNR), as shown in Table II;
3) average prediction errors per pixel, as shown in Table III;
4) average entropy of prediction errors, as shown in Table IV;
5) average percentage of unpredictable pels per frame (pels with absolute prediction errors larger than three, over a range of 255, are classified as unpredictable pels [3]), as shown in Table V;
6) average search points per block, as shown in Table VI.

Both BBGDS and PSA are implemented by assuming that the maximum iteration is eight. In the tables, $\text{GPS}_n(Count)$ is the proposed algorithm in which n represents the number of adjacent blocks used for gray prediction and $Count$ means

TABLE I
COMPARISON OF MSE OF THE SEARCH ALGORITHMS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average	Percentage
FS	360.93	357.59	350.35	268.85	135.14	28.71	16.31	216.84	100%
3SS	406.83	371.84	362.49	332.30	175.55	29.30	17.57	242.27	111.7%
CS	458.62	387.51	597.43	742.30	219.65	29.34	18.70	350.51	161.6%
PHODS	485.05	368.28	360.67	292.47	191.69	29.31	17.57	249.29	115.0%
4SS	406.26	363.78	358.68	298.03	156.53	29.30	17.57	232.88	107.4%
BBGDS	413.85	360.49	358.58	288.88	157.73	29.29	17.55	232.34	107.2%
SES	463.02	371.42	362.91	331.40	196.29	29.32	17.72	253.15	116.8%
PSA	395.78	360.23	360.11	284.32	161.48	29.30	17.56	229.83	106.0%
$GPS_4(8)$	391.27	358.99	357.99	278.86	157.12	29.29	17.57	227.30	104.8%
$GPS_4(10)$	386.33	358.99	357.92	278.84	155.01	29.29	17.57	226.28	104.4%
$GPS_4(12)$	383.99	358.99	357.85	278.84	154.16	29.29	17.57	225.81	104.1%
$GPS_3(8)$	392.70	359.10	357.87	282.68	156.61	29.29	17.54	228.58	105.1%
$GPS_3(10)$	391.90	359.10	357.80	282.66	154.64	29.29	17.54	227.56	104.9%
$GPS_3(12)$	389.64	359.10	357.73	282.66	153.84	29.29	17.54	227.11	104.7%

TABLE II
COMPARISON OF PSNR OF THE SEARCH ALGORITHMS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average	Percentage
FS	22.61	22.70	22.80	23.92	29.24	33.92	36.07	27.32	100%
3SS	22.09	22.51	22.65	22.98	28.07	33.86	35.80	26.85	98.3%
CS	21.55	22.34	20.44	19.44	27.24	33.85	35.59	25.78	94.4%
PHODS	21.32	22.55	22.67	23.56	27.47	33.86	35.80	26.75	97.9%
4SS	22.09	22.62	22.70	23.46	28.55	33.86	35.80	27.01	98.9%
BBGDS	21.99	22.61	22.70	23.61	28.58	33.86	35.80	27.02	98.9%
SES	21.52	22.51	22.64	23.00	27.64	33.85	35.76	26.70	97.7%
PSA	22.20	22.63	22.69	23.75	28.32	33.86	35.80	27.04	99.0%
$GPS_4(8)$	22.25	22.68	22.70	23.76	28.50	33.86	35.80	27.08	99.1%
$GPS_4(10)$	22.30	22.68	22.70	23.76	28.54	33.86	35.80	27.09	99.2%
$GPS_4(12)$	22.32	22.68	22.71	23.76	28.55	33.86	35.80	27.10	99.2%
$GPS_3(8)$	22.19	22.68	22.71	23.70	28.39	33.86	35.81	27.05	99.0%
$GPS_3(10)$	22.24	22.68	22.71	23.70	28.44	33.86	35.81	27.06	99.1%
$GPS_3(12)$	22.26	22.68	22.71	23.70	28.46	33.86	35.80	27.07	99.1%

TABLE III
COMPARISON OF PREDICTION ERRORS OF THE SEARCH ALGORITHMS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average	Percentage
FS	10.40	10.01	9.46	8.66	5.00	3.31	2.66	7.07	100%
3SS	11.00	10.19	9.64	9.87	5.77	3.31	2.69	7.50	106.0%
CS	11.58	10.37	12.66	15.19	6.33	3.31	2.73	8.88	125.6%
PHODS	11.88	10.12	9.61	9.03	6.00	3.31	2.69	7.52	106.3%
4SS	10.93	10.09	9.57	9.32	5.35	3.31	2.69	7.32	103.6%
BBGDS	10.95	10.05	9.56	8.96	5.39	3.31	2.69	7.27	102.9%
SES	11.64	10.18	9.65	9.87	6.06	3.32	2.70	7.63	107.9%
PSA	10.79	10.03	9.57	8.83	5.41	3.31	2.69	7.23	102.3%
$GPS_4(8)$	10.68	10.01	9.55	8.78	5.34	3.31	2.69	7.19	101.7%
$GPS_4(10)$	10.61	10.01	9.55	8.78	5.31	3.31	2.69	7.18	101.5%
$GPS_4(12)$	10.58	10.01	9.55	8.78	5.30	3.31	2.69	7.17	101.5%
$GPS_3(8)$	10.75	10.01	9.55	8.83	5.37	3.31	2.69	7.22	102.0%
$GPS_3(10)$	10.68	10.01	9.55	8.83	5.35	3.31	2.69	7.20	101.9%
$GPS_3(12)$	10.66	10.01	9.55	8.83	5.34	3.31	2.69	7.20	101.8%

the maximum iteration times. While the result of FS is set to 100%, the average percentages of results for other search algorithms are shown in the last "Percentage" column of the tables. According to the experimental results, the proposed GPS performs better than such algorithms as 3SS, CS, PHODS, 4SS, BBGDS, SES, and PSA in terms of the above six measures.

To further explore the accuracy of gray prediction, we compare the predicted motion vector, used to determine the initial search center, with the overall motion vector for PSA

TABLE IV
COMPARISON OF ENTROPY OF PREDICTION ERRORS OF THE SEARCH ALGORITHMS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average	Percentage
FS	5.66	5.50	5.39	5.37	4.40	4.13	3.83	4.90	100%
3SS	5.73	5.53	5.42	5.57	4.57	4.13	3.84	4.97	101.5%
CS	5.79	5.55	5.74	6.15	4.65	4.13	3.85	5.12	104.6%
PHODS	5.82	5.52	5.41	5.42	4.61	4.13	3.84	4.96	101.4%
4SS	5.71	5.51	5.40	5.49	4.47	4.13	3.84	4.94	100.8%
BBGDS	5.71	5.59	5.40	5.41	4.45	4.13	3.84	4.93	100.7%
SES	5.79	5.52	5.42	5.57	4.61	4.13	3.84	4.98	101.7%
PSA	5.71	5.53	5.40	5.42	4.49	4.13	3.84	4.93	100.7%
$GPS_4(8)$	5.68	5.50	5.40	5.38	4.47	4.13	3.84	4.91	100.4%
$GPS_4(10)$	5.68	5.50	5.40	5.38	4.47	4.13	3.84	4.91	100.4%
$GPS_4(12)$	5.67	5.50	5.40	5.38	4.47	4.13	3.84	4.91	100.3%
$GPS_3(8)$	5.69	5.50	5.40	5.39	4.48	4.13	3.84	4.92	100.4%
$GPS_3(10)$	5.69	5.50	5.40	5.39	4.48	4.13	3.84	4.92	100.4%
$GPS_3(12)$	5.69	5.50	5.40	5.39	4.48	4.13	3.84	4.92	100.4%

TABLE V
COMPARISON OF PERCENTAGE OF UNPREDICTABLE PELS OF THE SEARCH ALGORITHMS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average	Percentage
FS	59.5%	50.4%	48.5%	51.2%	34.7%	33.9%	25.0%	43.3%	100%
3SS	60.4%	50.8%	49.1%	55.0%	37.9%	33.9%	25.1%	44.6%	103.0%
CS	61.1%	51.2%	52.0%	62.0%	39.4%	33.9%	25.3%	46.4%	107.1%
PHODS	61.3%	50.6%	48.8%	52.1%	38.6%	33.9%	25.2%	44.4%	102.4%
4SS	59.8%	50.6%	48.6%	53.7%	36.0%	33.9%	25.1%	44.0%	101.5%
BBGDS	59.7%	50.9%	48.6%	51.9%	35.4%	33.9%	25.1%	43.6%	100.8%
SES	61.0%	50.8%	49.1%	55.0%	38.8%	33.9%	25.2%	44.8%	103.5%
PSA	60.2%	50.5%	48.6%	51.3%	35.8%	33.9%	25.1%	43.6%	100.7%
$GPS_4(8)$	59.7%	50.4%	48.5%	51.4%	35.6%	33.9%	25.1%	43.5%	100.5%
$GPS_4(10)$	59.7%	50.4%	48.5%	51.4%	35.6%	33.9%	25.1%	43.5%	100.5%
$GPS_4(12)$	59.7%	50.4%	48.5%	51.4%	35.6%	33.9%	25.1%	43.5%	100.5%
$GPS_3(8)$	59.9%	50.4%	48.5%	51.5%	35.8%	33.9%	25.1%	43.6%	100.6%
$GPS_3(10)$	59.8%	50.4%	48.5%	51.5%	35.8%	33.9%	25.1%	43.6%	100.6%
$GPS_3(12)$	59.8%	50.4%	48.5%	51.5%	35.7%	33.9%	25.1%	43.6%	100.6%

TABLE VI
COMPARISON OF SEARCH POINTS OF THE SEARCH ALGORITHMS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average	Percentage
FS	202.05	202.05	202.05	202.05	202.05	202.05	202.05	202.05	100%
3SS	23.13	23.03	23.17	23.22	23.11	23.02	23.05	23.10	11.4%
CS	15.45	15.42	15.56	15.49	15.49	15.47	15.47	15.48	7.7%
PHODS	13.35	13.33	13.37	13.39	13.35	13.33	13.34	13.35	6.6%
4SS	18.29	15.84	17.28	18.98	17.80	15.69	16.18	17.15	8.5%
BBGDS	14.53	10.95	11.67	13.97	12.31	8.48	9.65	11.65	5.8%
SES	16.23	16.88	16.27	15.87	16.24	16.95	16.67	16.45	8.1%
PSA	13.73	9.36	10.09	10.47	11.05	8.48	9.51	10.38	5.1%
$GPS_4(8)$	12.35	9.08	9.98	10.28	10.44	8.48	9.44	10.01	5.0%
$GPS_4(10)$	12.50	9.08	9.98	10.28	10.52	8.48	9.44	10.04	5.0%
$GPS_4(12)$	12.59	9.08	9.98	10.28	10.57	8.48	9.44	10.06	5.0%
$GPS_3(8)$	12.29	9.05	9.85	10.19	10.32	8.48	9.37	9.94	4.9%
$GPS_3(10)$	12.44	9.05	9.85	10.20	10.40	8.48	9.37	9.97	4.9%
$GPS_3(12)$	12.52	9.05	9.85	10.20	10.45	8.48	9.37	9.99	4.9%

and GPS, which are search algorithms based on the prediction of the initial search center. For each image block, when its predicted motion vector is equal to its overall motion vector, we call that a "hit." Thus, the average hit ratios for PSA and GPS are shown in Table VII, where the row "WP" represents the hit ratios without using any prediction method. Obviously, GPS achieves better prediction.

IV. CONCLUSIONS

An efficient gray prediction search algorithm for block motion estimation is presented in this paper. Using the gray system theory, the algorithm can determine the motion vectors of image blocks quickly and correctly. To reduce the implementation complexity and to prompt the prediction speed, the gray prediction procedure is implemented with the table-

TABLE VII
COMPARISON OF HIT RATIOS

	Football	Mobile	Windmill	Flower	Tennis	Salesman	Miss_A	Average
WP	40.8%	18.1%	19.4%	5.7%	53.0%	94.4%	59.6%	41.6%
PSA	40.9%	71.6%	53.0%	50.5%	58.1%	94.2%	63.2%	61.7%
$GPS_4(8)$	43.6%	74.4%	54.3%	51.2%	62.1%	94.4%	66.8%	63.8%
$GPS_3(8)$	43.6%	73.9%	54.1%	50.7%	61.9%	94.4%	66.8%	63.6%

lookup approach. The experimental results show that the proposed algorithm works better than other search algorithms. The VLSI architecture for the GPS algorithm is currently under development.

ACKNOWLEDGMENT

The authors wish to thank the editor and the anonymous reviewers for their valuable suggestions and careful review that helped to enhance the quality of the manuscript.

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