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Motion Vector Context-based Adaptive 3-D Recursive Search Block Matching Motion Estimation

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Abstract: - In this paper, based on the analysis to relationship between the currently being processed block and its neighbors, a motion vector context-based adaptive 3-D recursive search (MVCA-3DRS) block matching motion estimation algorithm is developed. In the proposed algorithm, the candidate vectors are partitioned into two categories, one stationary vector implying the current block belongs to one of neighboring large objects, one nonstationary vector implying the current block either belongs to one of neighboring small objects, or is a new object, then predicted with extended vector median estimator and anti-median estimator as well as random-updated estimator based on the spatial-temporal motion vector contexts. The simulation results show that the proposed algorithm can significantly improve the consistence of the resulting motion vector field. Test experiments on motion-compensation (MC) deinterlaced system with typical video sequences confirm that, compared with the 3DRS algorithm, the proposed MVCA-3DRS can significantly improve the interpolated images quality. Although introducing the additional vector filtering operations, the proposed algorithm still can maintain a comparative computation complexity with that of the 3DRS algorithm due to its shrink to the number of candidate vectors.

Key-Words: - 3DRS, block matching, motion estimation, de-interlace, frame rate up-conversion

1 Introduction

Block matching motion estimation plays a key role in video processing field. Except for widely used to video encoding such as the ITU-T/ISO/IEC standards for video coding [1,2], block matching motion estimation is also used to advanced video processing such as digital TV scan-format conversion, frame rate up-conversion, noise reduction, etc [3]. In video coding applications, it is used to provide a basic technique support for the hybrid block-based video coding framework of MPEG-x and H.26x standards. To yield as high coding efficiency as possible for video encoder, motion estimator only needs to minimize the block matching errors for a fixed-grid block partition. In advanced video processing applications, it is used to provide the true-motion information to perform MC interpolation for the lost image information. The true-motion poses a new challenge for motion estimation, and it requires the resulting motion vector field has inherent smoothness in addition to it minimizing block-matching errors. However, no one of the existing block matching estimation criterions including sum-of-absolute difference (SAD), mean square error as well as number of best matching pixels, can reflect the underlying smoothness constraint on the resulting motion vectors.

In [4], a true-motion estimation with 3-D recursive search (3DRS) block matching algorithm is proposed for the advanced video processing application. This novel algorithm first tactically constructed a limited vectors candidate set for every block from their three-dimensional spatial-temporal adjacent vectors in fixed sampling pattern based on asynchronous cyclic search principle, and then selected an optimal motion vector from the candidate vectors set by minimizing the SAD. Due to its peculiar neighboring prediction design scheme, the 3DRS algorithm not only fast converges to the true motion with high accuracy, but also maintains the smoothness of motion vectors.

It is well known that the shapes of motion objects are usually of complexity and levity. Just because of the simple fixed sampling pattern, the candidate vectors of 3DRS occasionally deviate the convergence direction, and the smoothness of the resulting vector fields therefore declines. Based on these observations, an MVCA-3DRS block matching motion estimation algorithm is developed in this paper. In the proposed algorithm, the candidate vectors will be partitioned into two categories, one stationary vector implying the current block belongs to one of neighboring large objects and one nonstationary vector implying the current block either belongs to one of neighboring small objects, or is a new object, then predicted with extended vector median estimator and anti-median estimator as well as random-updated estimator based on the spatial-temporal motion vector contexts.

The rest of this paper is organized as follows: Section 2 gives a brief overview to the 3DRS

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algorithm. Section 3 presents the detailed information about the proposed MVCA-3DRS algorithm, including the definition of (extended) vector (anti-)median filter, the selection of spatial-temporal context and the construction of the set of candidate vectors. The performance evaluation is reported in section 4 and finally conclusions drawn in section 5.

2 The 3DRS Block Matching Algorithm

In block-matching motion estimation algorithms, a displacement vector $\vec{D}(\vec{X},n)$ is assigned to the center $\vec{X}$ of every block $B(\vec{X})$ in current image n. Block matcher selects a displacement vector $\vec{D}(\vec{X},n)$ for every block from the search area $SA(\vec{X})$ limited by the candidate set $CS^{\max}$ based on optimum evaluation criterion, e.g. the commonly used SAD.

Formally, the candidate set $CS^{\max}$ of the full-search block matcher is defined as follows:

$$CS^{\max} = \{\vec{C} \mid -N \le C_x \le N, -M \le C_x \le M\} \qquad (1)$$

where N and M are constants limiting search area.

Rather than evaluating all possible candidate vectors, the 3DRS of [4] takes spatial and temporal prediction vectors from a 3-D neighborhood and a single updated prediction vector. Formally the candidate set $CS^{\max}$ of 3DRS block matcher is defined by

$$CS_{3DRS}(\vec{X},t) = \left\{ \begin{array}{l} \vec{C} \in CS^{\max} \mid \vec{C}_0 = \vec{0}, \\ \vec{C}_1 = \vec{D}(\vec{X} - (X,Y)^T, n), \\ \vec{C}_2 = \vec{D}(\vec{X} - (-X,Y)^T, n), \\ \vec{C}_3 = \vec{D}(\vec{X} + 2(-X,Y)^T, n-1), \\ \vec{C}_4 = \vec{D}(\vec{X} + 2(X,Y)^T, n-1), \\ \vec{C}_5 = \vec{C}_1 + \vec{U}_a(\vec{X},n), \\ \vec{C}_6 = \vec{C}_3 + \vec{U}_b(\vec{X},n) \end{array} \right\} \qquad (2)$$

where X and Y are the block width and height respectively, the update vector $\vec{U}_a(\vec{X},n)$ and $\vec{U}_b(\vec{X},n)$ are taken from a limited update set $US(\vec{X},n)$, which also contains quarter pixel values:

$$US(\vec{X},n) = US_i(\vec{X},n) \cup US_f(\vec{X},n)$$

$$US_i(\vec{X},n) = \{\vec{u}_y, -\vec{u}_y, \vec{u}_x, -\vec{u}_x, 2\vec{u}_y, -2\vec{u}_y, 3\vec{u}_x, -3\vec{u}_x\}$$

$$US_f(\vec{X},n) = \{\tfrac{1}{4}\vec{u}_y, -\tfrac{1}{4}\vec{u}_y, \tfrac{1}{4}\vec{u}_x, -\tfrac{1}{4}\vec{u}_x\}$$

where $\vec{u}_x = (1,0)^T$, $\vec{u}_y = (0,1)^T$.

The elements $\{\vec{C}_1, \vec{C}_2, \vec{C}_3, \vec{C}_4, \vec{C}_5, \vec{C}_6\}$ form a basic iterative set for the vector recursive search, where the random update vector $\vec{U}_a(\vec{X},t)$ and $\vec{U}_b(\vec{X},t)$ define the iterative step length. The null vector $\vec{0}$ makes the recursive search process instantly return to the zero point when encountering a stationary image parts. As a result, the 3DRS not only rapidly converges at the true-motion, but also obtain a high matching accuracy even in vicinity of discontinuities in vector plane.

3 The MVCA-3DRS Block Matching Motion Estimation

The true-motion vector field shows an abrupt variation only when a dissimilar motion object is found. Therefore, the block-based motion vector field presents smoothness provided the size of motion object greater than that of the block. Concretely, block motion vector shows either stationary statistical behavior with their neighboring counterparts when the current block is a part of a large-size object of the surrounding video objects, or nonstationary statistical behavior when the current block is a main part of a small-size object of the surrounding video objects or a new object.

Most of existing 3DRS algorithms [4~6] utilized these characteristics by using neighboring prediction with a fixed orthogonal-like spatial-temporal sampling pattern. Just the fixed sampling pattern results in drop of adaptation for the neighboring prediction to the complex shapes of video objects, therefore drop in prediction accuracy.

Based on the above observations to statistical behavior of motion vector, in this paper, a motion vector context-based adaptive neighboring prediction is developed to fix this fault. The proposed algorithm is therefore referred to as MVCA-3DRS block matching algorithm. In MVCA-3DRS algorithm, an extended vector median estimator and an extended vector anti-median estimator as well as a random-updated median estimator are respectively used to predict the spatial/temporal stationary- and nonstationary-vectors based on the spatial/temporal context. Before presenting the new scheme, vector median filter and anti-median filter as well as their extensions are first described.

3.1 Vector median filter and its extension

Definition 1 suppose samples $\vec{a}_j \in R^2$, $1 \le j \le N$, the operator $\mathbf{F}_M$ is said to be vector median filter, if only if

$$\mathbf{F}_M\{\vec{a}_1, \vec{a}_2, \ldots, \vec{a}_N\} \equiv \vec{a}_M \qquad (3)$$

and $\vec{a}_M$ satisfying $\vec{a}_M \in \{\vec{a}_1, \vec{a}_2, \ldots, \vec{a}_N\}$

$$\text{and } \sum_{n=1}^{N} \|\vec{a}_M - \vec{a}_n\|_L \le \sum_{n=1}^{N} \|\vec{a}_j - \vec{a}_n\|_L, \ \forall\ j \in \{1, \ldots, N\} \qquad (4)$$

where $\|\bullet\|_L$ denotes the L norm of R^2 space. ■

It is easy to prove that the vector median $\vec{a}_M$ using the L_1 norm or L_2 norm is the maximum likelihood estimator for the source, based on the random samples $\{\vec{a}_1,\vec{a}_2,...,\vec{a}_N\}$ from a population having exponential distributions or biexponential distributions respectively [7]. Obviously, vector median filter has typical low-pass character.

Definition 2 suppose samples $\vec{a}_j \in R^2$, $1 \le j \le N$, the operator $\mathbf{F}'_M$ is said to be a extended vector median filter, if only if

$$\mathbf{F}'_M\{\vec{a}_1,\vec{a}_2,...,\vec{a}_N,\vec{a}_{N+1}\} \equiv \vec{a}_M \tag{5}$$

and $\vec{a}_M$ satisfying $\vec{a}_M \in \{\vec{a}_1,\vec{a}_2,...,\vec{a}_N,\vec{a}_{N+1}\}$

$$\text{and} \sum_{n=1}^{N+1}\|\vec{a}_M-\vec{a}_n\|_L \le \sum_{n=1}^{N+1}\|\vec{a}_j-\vec{a}_n\|_L \text{ , } \forall\ j \in \{1,...,N+1\} \tag{6}$$

$$\text{where } \vec{a}_{N+1} = \frac{1}{N}\sum_{j=1}^{N} a_j \text{ .}$$ ■

The experiments show that extended vector median filter has much more robust than its counterpart. For convenience, the operator $\mathbf{F}_M$ is hereinafter referred to as extended vector-median filter instead of vector-median filter.

3.2 Vector anti-median filter and its extension

Definition 3 suppose samples $\vec{a}_j \in R^2$, $1 \le j \le N$, the operator $\mathbf{F}_{AM}$ is said to be vector anti-median filter, if only if

$$\mathbf{F}_{AM}\{\vec{a}_1,\vec{a}_2,...,\vec{a}_N\} \equiv \vec{a}_M \tag{7}$$

and $\vec{a}_M$ satisfying $\vec{a}_M \in \{\vec{a}_1,\vec{a}_2,...,\vec{a}_N\}$

$$\text{and} \sum_{n=1}^{N}\|\vec{a}_M-\vec{a}_n\|_L \ge \sum_{n=1}^{N}\|\vec{a}_j-\vec{a}_n\|_L \text{ , } \forall\ j \in \{1,...,N\} \tag{8}$$

■

It can be proved that the vector anti-median $\vec{a}_M$ using the L_1 norm or L_2 norm is the maximum likelihood estimator for the source with max-bias, based on the random samples $\{\vec{a}_1,\vec{a}_2,...,\vec{a}_N\}$ from a population having exponential distributions or biexponential distributions respectively. In contrast to vector median filter, vector anti-median filter has typical high-pass character.

Definition 4 suppose samples $\vec{a}_j \in R^2$, $1 \le j \le N$, the operator $\mathbf{F}'_{AM}$ is said to be an extended vector anti-median filter, if only if

$$\mathbf{F}'_{AM}\{\vec{a}_1,\vec{a}_2,...,\vec{a}_N,\vec{a}_{N+1}\} \equiv \vec{a}_M \tag{9}$$

and $\vec{a}_M$ satisfying $\vec{a}_M \in \{\vec{a}_1,\vec{a}_2,...,\vec{a}_N,\vec{a}_{N+1}\}$

$$\text{and} \sum_{n=1}^{N+1}\|\vec{a}_M-\vec{a}_n\|_L \ge \sum_{n=1}^{N+1}\|\vec{a}_i-\vec{a}_n\|_L \text{ , } \forall\ j \in \{1,...,N+1\} \tag{10}$$

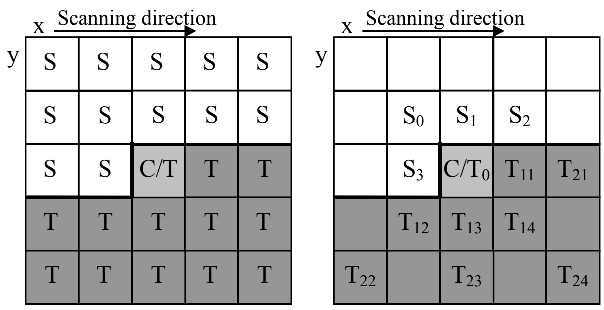
$$\text{where } \vec{a}_{N+1} = \frac{1}{N}\sum_{j=1}^{N} a_j \text{ .}$$ ■

The experiments show that extended vector anti-median filter has also much more robust than its counterpart. For convenience, the operator $\mathbf{F}_{AM}$ is hereinafter referred to as extended vector anti-median filter instead of vector anti-median filter.

3.3 Vector Context sampling

For every scanning position of 3DRS algorithm, the spatial motion vectors and the temporal motion vectors form a complementary full plane in MV memory as shown in figure 1(a). In the spatial half-plane, the block S_0, S_1, S_2 and S_3 shown in figure 1(b) are the nearest spatial vicinity of the block currently being processed, hence their corresponding vectors should be sampled as the spatial context $\mathbf{D}(\vec{X},t)$ of currently being estimated vector, i.e.

$$\mathbf{D}(\vec{X},t) = \left\{ \begin{matrix} \vec{D}(\vec{X}-(X,Y)^T,t), \vec{D}(\vec{X}-(0,Y)^T,t), \\ \vec{D}(\vec{X}-(-X,Y)^T,t), \vec{D}(\vec{X}-(X,0)^T,t) \end{matrix} \right\} \tag{11}$$



(a) (b)

Fig.1 MV structure in memory

Due to the time difference of adjacent frames/ fields, the temporal reference block T_0 does not always correspond to the spatial current block C. Hence in the temporal half-plane, the block T_{21}, T_{22}, T_{23} and T_{24} in addition to the block T_0, T_{11}, T_{12}, T_{13} and T_{14} also would be the neighbors of current block. To shrink the number of context elements, a five-points sampling scheme is employed to yield the temporal context for the current vector, i.e.

$$\mathbf{D}(\vec{X},t-1) = \left\{ \begin{matrix} \vec{D}(\vec{X},t-1), \\ \vec{D}(\vec{X}+r\cdot(X,0)^T,t-1), \\ \vec{D}(\vec{X}+r\cdot(-X,Y)^T,t-1), \\ \vec{D}(\vec{X}+r\cdot(0,Y)^T,t-1), \\ \vec{D}(\vec{X}+r\cdot(X,Y)^T,t-1) \end{matrix} \right\} \tag{12}$$

where r denotes the distance parameter for block shifting. Similar to [4], $r = 2$ has been experimentally found to be best for a block size of 8×8 pixels.

3.4 Construction of Candidate Vectors Set for MVCA-3DRS algorithm

Based on the spatial context $\mathbf{D}(\vec{X},t)$, we can define three different estimators for the current vector with vector filtering operators, i.e.

$$\begin{cases} \hat{\vec{D}}_1^S = \mathbf{F}_M \mathbf{D}(\vec{X},t) \\ \hat{\vec{D}}_2^S = \mathbf{F}_{AM} \mathbf{D}(\vec{X},t) \\ \hat{\vec{D}}_3^S = \mathbf{F}_M \mathbf{D}(\vec{X},t) + \vec{U}_S \end{cases} \tag{13}$$

where $\vec{U}_S$ denotes the spatial update vector.

The spatial extended vector median estimator $\hat{\vec{D}}_1^S$ suggests that the block currently being estimated belongs to one large-scale object of its spatial neighbors. The spatial extended vector anti-median estimator $\hat{\vec{D}}_2^S$ suggests that the block currently being estimated belongs to one small-scale object of its spatial neighbors. The spatial updated estimator $\hat{\vec{D}}_3^S$ suggests that the current block is a new object.

Similarly based on the temporal context, three temporal estimators can be defined for the current vector with vector filtering operators. However, due to the time difference between adjacent frames/fields, the temporal extended vector anti-median estimator likely implies a case for a neighbor of current block, thus is not reliable as the temporal predictor of current vector. Therefore, based on the temporal context $\mathbf{D}(\vec{X},t-1)$, only two estimators are defined for the current vector, i.e.

$$\begin{cases} \hat{\vec{D}}_1^T = \mathbf{F}_M \mathbf{D}(\vec{X},t-1) \\ \hat{\vec{D}}_2^T = \mathbf{F}_M \mathbf{D}(\vec{X},t-1) + \vec{U}_T \end{cases} \tag{14}$$

where $\vec{U}_T$ denotes the temporal update vector.

Based on the above-defined estimators, we finally arrive at a candidate set, which consists of the spatial extended vector median estimator, the spatial extended vector anti-median estimator, a spatial updated estimator, a temporal extended vector median estimator, a temporal updated estimator, and a null vector. Mathematically, this set of six motion vector candidates constructed with motion vector contexts, $CS_{3DRS}^{MVCA}(\vec{X},t)$ can be described as follows:

$$CS_{3DRS}^{MVCA}(\vec{X},t) = \begin{Bmatrix} \vec{C} \in CS^{\max} \mid \vec{C}_0 = \vec{0}, \\ \vec{C}_1 = \mathbf{F}_M \mathbf{D}(\vec{X},t), \\ \vec{C}_2 = \mathbf{F}_{AM} \mathbf{D}(\vec{X},t), \\ \vec{C}_3 = \mathbf{F}_M \mathbf{D}(\vec{X},t-1) \\ \vec{C}_4 = \vec{C}_1 + \vec{U}_S \\ \vec{C}_5 = \vec{C}_3 + \vec{U}_T \end{Bmatrix} \tag{15}$$

where the spatial update vector $\vec{U}_S$ and the temporal update vector $\vec{U}_T$ are chosen cyclically from the predefined spatial update set US_S and temporal update set US_S respectively.

$$US_S = \{\tfrac{1}{4}\vec{u}_x, \tfrac{1}{4}\vec{u}_y, -\tfrac{1}{4}\vec{u}_x, -\tfrac{1}{4}\vec{u}_y\}$$

$$US_T = \{\tfrac{1}{4}\vec{u}_x, \tfrac{1}{4}\vec{u}_y, -\tfrac{1}{4}\vec{u}_x, -\tfrac{1}{4}\vec{u}_y, 2\vec{u}_x, 2\vec{u}_y, -3\vec{u}_x, -3\vec{u}_y\}$$

Small-scale variation of spatial update vector is expected to improve the spatial smoothness of motion vector field. Large-scale variation of temporal update vector is expected to accelerate the convergence speed of recursive search.

Compared with 3DRS algorithm, the proposed algorithm increases the operations of vector filtering processing. Note the norm-calculation elements of extended vector median filtering and anti-median filtering can be multiplexed used, and the number of candidate vector is also shrunk to six. The computation complex of the proposed algorithm therefore still can be maintained at a comparative level with that of 3DRS algorithm.

4 Algorithm Evaluations

In this section, the proposed algorithm which use the candidate set defined by the formula (15) is compared with the 3DRS algorithm which use a set of seven motion vector candidates as given by the formula (2). The L_1 norm is employed for the proposed algorithm to calculate the extended vector (anti-)median filtering. Algorithms are evaluated with three typical test sequences shown on Fig. 2.

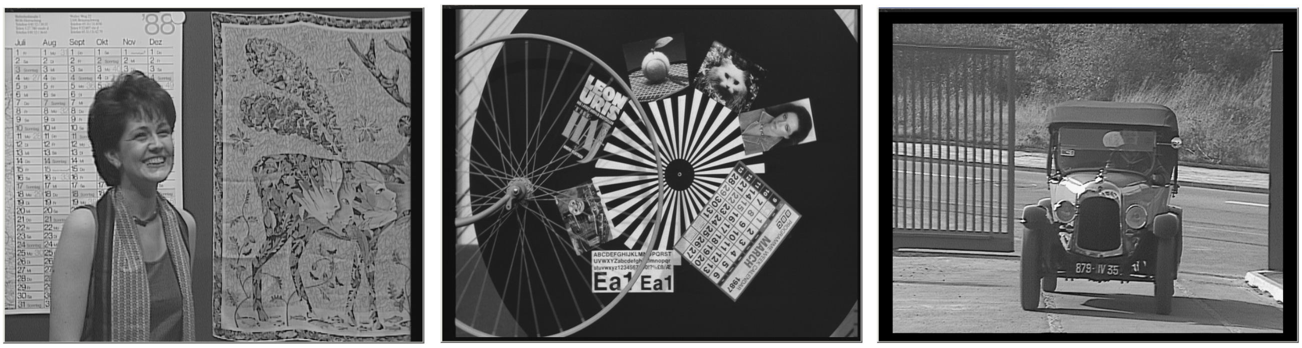
4.1 Improvement of Smoothness of MV Field

In MC interpolation application, the spatial consistence of the estimated displacement vector field is a key factor to affect the quality. To quantify the effects of different algorithms on the consistence of estimated motion vector field, the resulting motion vector field is evaluated with a smoothness figure $S(t)$ similar to that of [4], defined as following:

$$\mathrm{S}(t) = \frac{8 * N_B}{\sum_{\vec{X} \in MW} \sum_{i=-1}^{1} \sum_{j=-1}^{1} \left\| \vec{D}(\vec{X},t) - \vec{D}(\vec{X} + (i \cdot X, j \cdot Y)^T, t) \right\|_{L_1}} \tag{16}$$

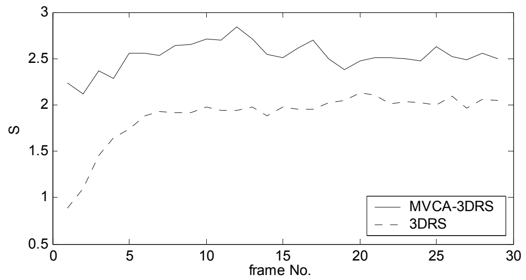
where $\vec{X}$ run through all center of the blocks within the measure window of a picture, N_B is the number of blocks in measure window.

Fig. 3 gives the value of smoothness figure *S*(*t*) vs. the number of fields of test sequences for different algorithms. These experiments results show that the proposed algorithm can significantly improve the consistence of the resulting motion vector field due to its adaptively separative prediction method. Thus, it can be expected that the

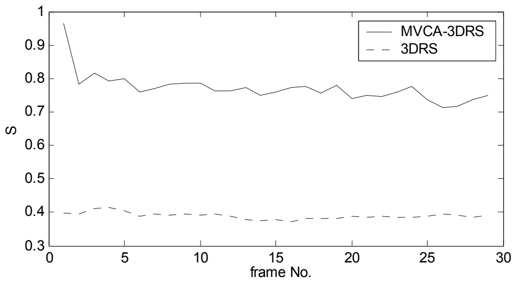


(a) Renata (b) Bicycle (c) Car&Gate

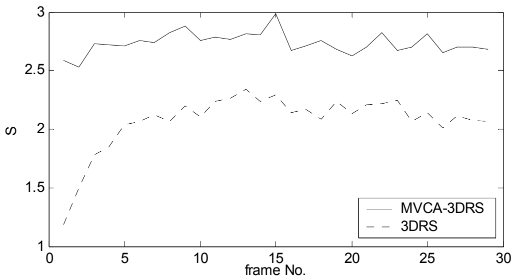
Fig. 2. Pictures from each test sequence



(a) Renate



(b) Bicycle



(c) Car&Gate

Fig. 3. Smoothness results comparison

proposed algorithm can improve the MC interpolated image quality.

4.2 Application Case

To confirm the foresaid assumption, in this subsection, the proposed algorithm is applied to a MC deinterlacing system sketched by Fig.4.

As shown in Fig.4, the progressive video sequence is input to interlacing generator block, in which the progressive sequence is separated into two complementary interlaced sequences, and one interlaced sequence is used to perform MC deinterlacing, one

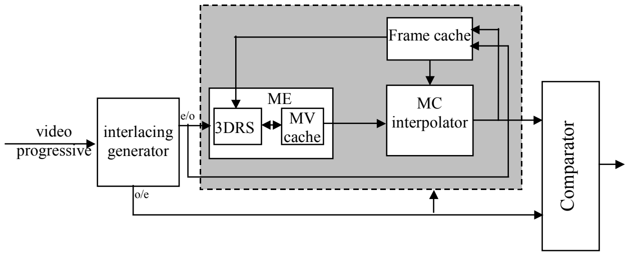


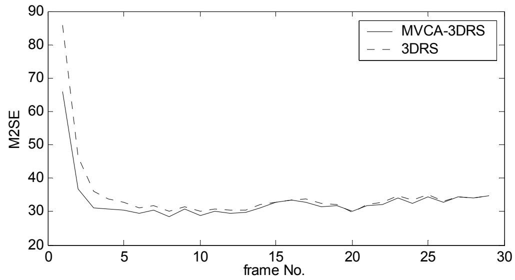
Fig. 4 Block scheme of simulation experiments system

used for the original reference. In the motion estimation block, the input interlaced field is first partitioned into 8×4 blocks, the (MVCA-)3DRS estimator then performs block matching estimation on every current block based on the reference frame and the spatial-temporal motion vectors, and at last the resulting vector is written back to the MV cache. In the MC interpolator block, a MC deinterlacing interpolation is performed on the input interlaced sequence based on the estimated vector and the reference frame. To eliminate blocking effects and further improve the interpolated image quality, the block erosion of [4] and vertical median filtering are respectively applied to the input MV and the resulting interpolated pixels. In the comparator block, the MC interpolated sequence is compared with the original reference sequence by a performance criterion function. Here a modified mean square error (M2SE) is selected to evaluate the performance of a motion estimator, and M2SE defined as

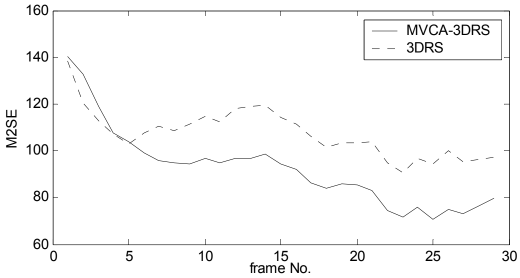
$$\mathrm{M2SE}(t) = \frac{1}{N_{MW}} \sum_{\vec{X} \in MW} \left(f(\vec{X},t) - \hat{f}(\vec{X},t) \right)^2 \qquad (17)$$

where $f(\vec{X},t)$ is the original image pixel, $\hat{f}(\vec{X},t)$ is the interpolated image pixel, N_{MW} is the number of pixels within Measurement Window.

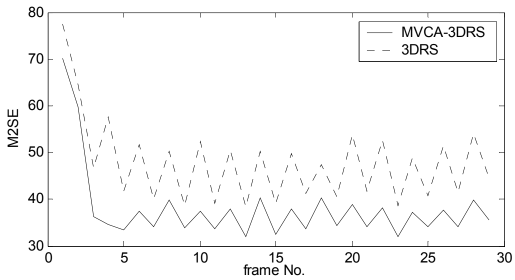
Fig. 5 presents the value of M2SE(t) vs. the number of fields of the test sequences for the proposed algorithm and the 3DRS. It clearly shows that the proposed MVCA-3DRS algorithm significantly improves the interpolated image quality, especially for these sequences with complex motion objects, such as the sequence "Bicycle" and



(a) Renata



(b) Bicycle



(c) Car&Gate

Fig. 5. M2SE results Comparison

"Car&Gate".

Fig.5(c) show that the proposed algorithm still can't eliminate the jitter of curve due to lack of particular consideration to the camera motion such as pan, tilts and travels of the camera and zooming with its lens. Therefore, in future the parametric candidate of [5] can be taken into consideration to be added to the proposed candidate set to overcome this bad case.

5 Conclusion

In this paper, we present a high-performance block matching motion estimation fast algorithm oriented to MC interpolation application. It essentially can be looked as a variation of the famous 3DRS algorithm. In the proposed algorithm, the candidate vectors are partitioned into two categories, one stationary vector implying the current block belongs to one of neighboring large objects and one nonstationary vector implying the current block either belongs to one of neighboring small objects, or is a new object, then predicted with extended vector median estimator and anti-median estimator as well as random-updated estimator based on the spatial-temporal motion vector contexts.

The simulation experiments results show that the proposed algorithm can significantly improve the smoothness of the resulting motion vector field. Test results on a MC deinterlacing system confirm that the proposed algorithm also surely significantly improve the MC interpolated image quality in practice. Due to the shrink to the number of candidates, the proposed algorithm still maintain a comparative computation complexity with that of 3DRS although it increasing the extended vector (anti-)median filtering operations.

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References:

[1] T. Sikara, MPEG digital video-coding standards: delivering picture-perfect compression for storage, Transmission, and Multimedia Application. *IEEE Signal Processing Magazin*e, Vol.14, No.5, 1997, pp82-100.

[2] ITU-T Recommendation H.263 (1996) Video coding for low bit rate communication.

[3] G. de Haan, "Progress in motion estimation for consumer video format conversion," *IEEE Transactions on Consumer Electronics,* Vol. 46, No.3, 2000, pp.449-459.

[4] G. de Haan, P.W.A.C Biezen, H. Huijgen, and O.A. Ojo, "True Motion Estimation with 3-D Recursive Search Block-Matching,"*IEEE Trans. on Circuits and Systems for Video Technology (CVST)*, Vol.3, No.5, 1993, pp.368-388.

[5] G. de Haan and P.W.A.C. Biezen, "An efficient true-motion estimator using candidate vectors from a parametric motion model," *IEEE Trans. on CVST,* Vol.8, No.1, 1998, pp.85-91.

[6] A. Beric, G. de Haan, R. Sethuraman, and J. van Meerbergen "A technique for reducing complexity of recursive motion estimation algorithm," *Proc. SIPS, IEEE Workshop on Signal Processing Systems,* Seoul, South Korea, August 27-29, 2003, pp. 195-200.

[7] J. Astola, P. Haavisto and Y. Neuvo, "Vector median filters," *Proceedings of the IEEE,* Vol.78, No.4, 1990, pp.678-689.