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Block compressed sensing of video based on unstable sampling rates and multihypothesis predictions

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ABSTRACT

Existing divide block video compression perception is usually used the same measurement matrix measure for all image block, the average distribution of sampling rate measurement method ignores at different areas of the structure complexity and change degree different of the facts in the video. In order to solve this problem, this paper proposed an adaptive allocation sampling rate of the unstable sampling rate compression method by the distribution characteristics of the video inter-frame correlation. Categorizing the size of the image block according to the inter-frame correlation and assign different sampling rates, refactoring process adopt the unstable sampling rate multihypothesis predictions algorithm to make full use of the inter-frame correlation. Experimental results show that this paper's algorithm can reconstruct the high quality video images under low sampling rate, and the unstable sampling rate measurement method is helpful to improve the refactoring quality of sports areas

KEYWORDS

Compressed sensing(CS);
Unstable sampling rates;
Adaptive sampling;
Inter-frame correlation;
Multihypothesis prediction.

INTRODUCTION

Compressed Sensing theory (Compressed Sensing, CS) by Donoho, Candes and Chinese scientists Tao and others scientists put forward in 2004, Candes et al.[1] in 2006, from mathematics to justifying the part from Fourier transform coefficient accurately reconstruct the original signal, and laid a theoretical basis for compression perception. Because of the high resolution mathematics images and video frequency band math wider, based on the Shannon theorem for sampling before compression of traditional data processing method is causing serious waste of sampling resources[2]. Compressed sensing theory, combined the traditional data acquisition and data compression in the process of signal acquisition for the least coefficient to describe the signal, and to the use of sparse sex or in low rank[3,4] such as prior knowledge from the known to a small number of measured value by reconstruction algorithm to reconstruct the original signal with high probability[5,6].

Video compression sampling process can be realized through continuous use single pixel camera[7], the whole frame sampling method will lead to the storage space and algorithm complexity of the problem. To do this, the literature[8] proposed a piece of sampling mode,

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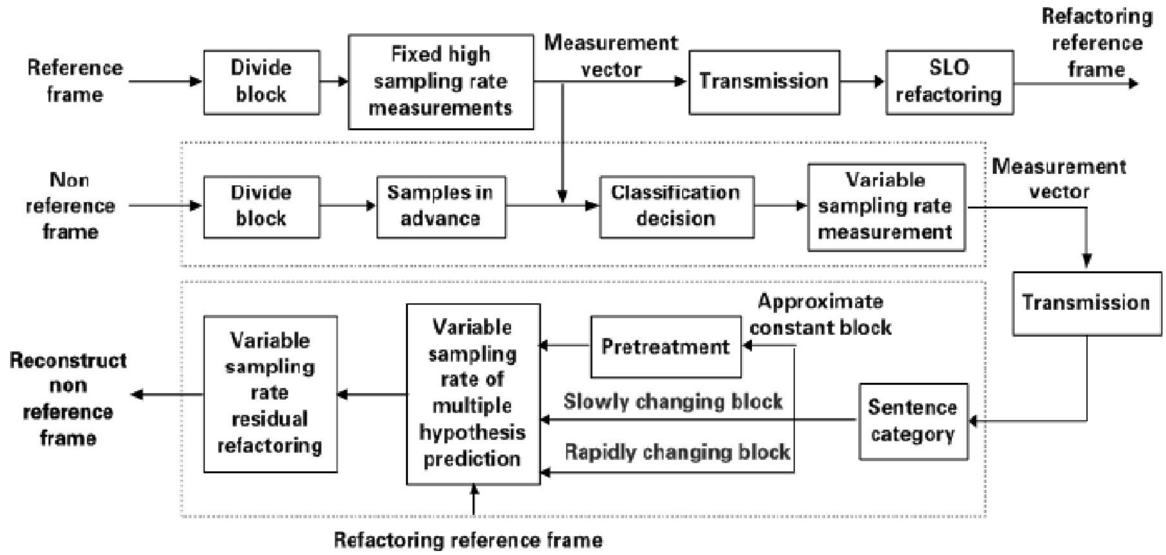

Figure 1 : Video compression perception structure based on variable sampling rate

the single frame image block and the blocks are all use the same measurement matrix sample separately. And directly compared to the reconstruction of the whole image sampling method, in view of the single frame reconstruction algorithm of block sampling on the speed and quality are shows obvious superiority[9,10]. However, these in a video single frame processing method ignores the video of the strong correlation between successive frames. Based on the motion estimation and motion compensation of the video compression perception reconstruction algorithm not only takes advantage of the video inter-frame correlation, and transfer to the traditional video compression coding complexity in the decoding side, reduces the power consumption and cost of the video acquisition device[11,12]. Video compression perception of motion estimation process is at the receiving end use the measured value of the known crude reconstructed with visible noise approximation of the frame, then to predict motion estimation. By contrast, Tramel et al.[13,14] is put forward in the measurement field directly predict more assumption frame prediction method (MultiHypothesis Frame Prediction, MHFP) can significantly improve the accuracy of forecasting frame. But due to ignore movement characteristics of different regions in the video scene, this method for utilization rate of the inter-frame correlation remains to be improved. The literature[15] although aware of the problem, but because of when the adaptive sampling need periodically joined the reflectorizing process and greatly increases the sampling of the complexity, contrary to the original intention of compression perception theory.

Considering the inter-frame correlation different between different regions of the video sequence, this paper proposes a simple and effective divide block video compression perception algorithm based on variable sampling rate. First, the same measurement matrix are used to get the target frame and reference frame corresponding measurement vector, according to the difference between the energy block can be divided into three categories: approximate constant block0slowly changing block and rapidly changing block. Second, different categories of block are processed by choose different sampling rate respectively. This kind of measurement method can according to different blocks has different scene complexity and change intensity of adaptive adjust their measuring points (that is block sampling rate), so as to achieve the aim of reasonable distribution of sampling rate.

At the receiving end, this paper through the multihypothesis prediction of variable sampling rate to get frames of prediction, and based on the residual redundancy dictionary ε regularization forms of iterative weighted least-square method (ε-regularized Iteratively Reweighed Least Squares, ε-regularized IRLS) refactoring to predict residual, finally get the high quality of the reconstructed frames. This paper put forward video compression perception based on the variable sampling rate measurement of structure specific process as shown in Figure 1.

VARIABLE SAMPLING RATE MEASUREMENT OF VIDEO SEQUENCES

Reference frame of fixed high sampling rate measurements

The single frame image for $n \times n$, if as a $n^2 \times 1$ of vector direct sampling, The $m \times n^2$ of measurement matrix is needed to get m measured values, obviously the scale of the measurement matrix storage and computing will bring great difficulty in video compression perception system. This paper's literature[8] puts forward the block sampling mode, will get K $B \times B$ blocks by reference frames not overlap division block, and for each image block with the same measurement matrix Φ separate sampling. For the NO. $i = 1,2,\cdots,K$ image block x_{t-1}^i, the measurement vector can be represented as:

$$y_{t-1}^i = \Phi x_{t-1}^i \tag{1}$$

In the formula $\Phi \in R^{M \times N}(M = \left[(mN)/n^2\right], N = B^2), y_{t-1}^i \in R^{M \times 1}$. The whole reference frame of sampling process can be expressed as $Y_{t-1} = \Phi X_{t-1}$, among them $X_{t-1} \in R^{N \times K}$ and $Y_{t-1} \in R^{M \times K}$'s column vector respectively for each image block's pixel vector and measurement vector.

In order to be able to better satisfy the quality reconstruction requirement of the video compression perception, this paper adopts the K-SVD (K-Singular Value Decomposition) method training 4 times redundant dictionary makes video signal's sparse representation of the coefficient is more sparse under the dictionary:

$$x_{t-1}^i = \Psi \alpha_{t-1}^i \tag{2}$$

In the formula Ψ for the KSVD dictionary, α_{t-1}^i for the coefficient of sparse representation. In addition, the design of the measurement matrix is Φ also the important issues of compressed perception theory. In this article, it is adopts KSVD dictionary Ψ to obtain the best measure by optimization criterion. The key of design best measurement matrix is make the holographic base $\Theta = \Phi\Psi$'s cross correlation of the atom minimum, namely to construct a measurement matrix Φ satisfy the rule of optimization: $\Theta^T\Theta \approx I$.

Non reference frame of the variable sampling rate measurement

Different moving objects in video may movement in different ways, so the inter-frame correlation between different areas is different. For measuring of non reference frame, the article according to different degree of change of relative reference frame in different regions of the reasonable distribution of sampling rate in order to obtain high efficient sampling, which changes degree smaller regional distribution of low sampling rate, which changes degree bigger regional distribution of higher sampling rate, so ensure the area of rapid change at low speeds of under total sampling rate can still high quality reconstructed. When the scene occurrence mutated, using this article's proposed variable sampling rate for sampling, almost all blocks will be at the highest sampling rate for sampling, can ensure a mutations scene of high quality reconstruction.

Classification sentences standard

Take non reference frame divide block by not overlapped in the same way as reference frame, the NO. i block x_t^i and the difference of the among corresponding position's x_{t-1}^i in the reference frame reflects on the position of the inter-frame correlation, namely two corresponding block of the residual energy size $E(x_{t-1}^i, x_t^i) = \| x_{t-1}^i - x_t^i \|_2^2$ can be used as judgment criterion of block classification. However, due to the brightness of different video and contrast of different video is large, the corresponding residual energy can make a big difference, as judgment criterion when the decision threshold choice for the dependence of the video will be very strong, thus affecting algorithm versatility. Therefore, this article uses the residual and the reference block's energy ratio as the judgment criterion.

$$e(x_{t-1}^i, x_t^i) = \frac{E(x_{t-1}^i, x_t^i)}{E(x_{t-1}^i)} \tag{3}$$

It is important to note that the video frame of pixel values in compressed sensing system is unknown, only known to the measured values. So this article uses the residual energy of measurement domain and the ratio

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of the reference block energy as decision criteria.

$$e(y_{t-1}^{i}, y_{t}^{i}) = \frac{E(y_{t-1}^{i}, y_{t}^{i})}{E(y_{t-1}^{i})} \tag{4}$$

To the Foreman, News, Susie, Football, Caltrain, Garden, Tempete and Tennis total 8 sets standard video sequence of 12968 image block using threshold value T_1 and T_2 for classification ($T_1 < T_2$). According to the formula (3) calculate the NO. i block of the pixel domain decision function value, if $e(x_{t-1}^{i}, x_{t}^{i}) < T_1$, then this block of judgment for the approximate constant block. Calculated all the approximate constant block of the measurement domain decision function value by the formula (4), if meet $e(y_{t-1}^{i}, y_{t}^{i}) < T_1$, the indicates that using of measurement domain decision function can be classified correctly. To meet $T_1 \le e \le T_2$ of the slowly changing block and meet $e > T_2$ of the rapidly changing block's measurement domain of the decision function whether realize correct classification's test method in the same way. The statistical results showed that in the pixel domain decision function to determine the approximate constant block according to the measurement field classified decision the probability of correctly for 93.35%, slowly changing block and rapidly changing block classified the probability of correctly for 89.68% and 97.02% respectively. Experiments show that the residual energy ratio of measurement domain can reflect the changes of pixel domain really, and can realize correct classification.

Variable sampling rate measurement

Supposing approximate constant block,slowly changing block and rapidly changing block of sampling rate respectively for S_1, S_2 and S_3, among them S_3 and the reference frame of block sampling rate is the same, and $S_1 < S_2 < S_3$, the corresponding block sampling points respectively for $M_1 = [S_1 \cdot B^2]$, $M_2 = [S_2 \cdot B^2]$ and M.

First, take the non reference frame for pre-sampling. The pre-sampling matrix Φ_2 is constituted by measured matrix Φ of the reference frame of former M_2 lines, take the non reference frame of image block x_t^i for projection to get measure value $y_{t,M_2}^{i} = \Phi_2 x_t^i$. Then compared to the pre-sampling value y_{t,M_2}^{i} and the reference frame measure value of former M_2 lines y_{t-1,M_2}^{i}, and according to the setting threshold T_1 and T_2, carries on the classification decision.

Calculated x_t^i of the decision function value e by the formula (4), if $e < T_1$, then it is judgment for approximate constant block, only keep among of the measurement vector former M_1 measure value to get y_{t,M_1}^{i}, which reduced the block sampling rate to S_1; if $T_1 \le e \le T_2$, then it is judgment the block for slowly changing block, keep M_2 measure value unchanged, sampling rate is still S_2; if $e > T_2$, then it is judgment for rapidly changing block, increase the sampling rate to S_3, that is formula (5) and formula (6) to increase its measurement vector length, get the new measurement vector $y_{t,M}^{i}$:

$$\Delta y_t^i = \Phi_\Delta x_t^i \tag{5}$$

$$y_{t,M}^{i} = \left[(y_{t,M_2}^{i})^T, (\Delta y_t^i)^T \right]^T \tag{6}$$

Among of them, Φ_Δ is the composition of additional measurement matrix by measurement matrix of $M_2 + 1 \sim M$ lines.

In order to ensure the formula (4) was used as the classification decision function to realize accurate classification, need pre-sampling y_{t,M_2}^{i} can correctly reflect the reality changes of the current block, namely the measurement vector of information should be large enough, the pre-sampling process can not be able to use too low sampling rate, and pre-sampling rate is too high will affect the sampling speed. Therefore need to moderate choose pre-sampling rate, achieve both can reduce the risk of misclassification and can avoid the sampling speed is affected. 2.2.1 section of the correct classification statistical results is got by pre-sampling rate for 20%, the correct classification probability is higher, and sampling speed is moderate.

Because of this article's variable sampling rate measurement process is adaptive, we do not know the real sampling rate of the non reference frame in advance, therefore in the process of actual transmission, each block need more transmit a data used to record the block categories. But these additional data in the process of actual transmission to increase the extra burden is not obvious, if each measured values expressed in 1 byte, and use the binary number 01, 10 and 11 respectively the No.1, 2, 3 classes, the each block with

2 bit transmission its category information. The actual sampling rate of non reference frame are as follows:

$$S = \frac{K_1 \times M_1 + K_2 \times M_2 + K_3 \times M + K/4}{n^2} \quad \textbf{(7)}$$

In the formula, n^2 shows the total pixel number of non reference frames, K shows the total number of divide block, K_1 shows the number of sentence as class 1 image block, K_2 shows the number of sentence as class 2 image block, K_3 shows the number of sentence as class 3 image block, and meet $K = K_1 + K_2 + K_3$.

THE RE-FACTORING BASED ON SAMPLING RATE OF MEASUREMENT VALUE

Reference frame of smooth ℓ_0 Norm re-factoring

The high sampling rate measurement of fixed reference frame, direct application of single frame compression perception of rapid reconstruction algorithm can get high quality reconstruction results. Due to measurement number M is less than the length of signal N, from $y_{t-1}^i = \Phi x_{t-1}^i$ in solution x_{t-1}^i is the solving problem of non only solution of the undetermined equations. Using video signal under the dictionary Ψ has a sparse representation of prior knowledge, take the problem of solve the undetermined equations to be transformed to the minimum 0-norm problem:

$$\hat{\alpha}_{t-1}^i = \arg\min \| \hat{\alpha}_{t-1}^i \|_{0,} \ \text{s. t. } y_{t-1}^i = \Phi \Psi \alpha_{t-1}^i \quad \textbf{(8)}$$

In the formula, $\| \hat{\alpha}_{t-1}^i \|_0$ shows the number of the non zero elements of sparse coefficient, namely the sparse degree. And uses $\hat{x}_{t-1}^i = \Psi \hat{\alpha}_{t-1}^i$ to get reconstructing signal $\hat{x}_{t-1}^i$.

However, the solution of the minimum ℓ_0 norm is a NP-hard problem, can be transformed into minimum ℓ_1 norm or smooth ℓ_0 norm (Smoothed ℓ_0, this article defined its SL0 norm) of optimal solution. This paper chooses to solve the minimum SL0 norm method to quickly and accurately reconstruct reference frame:

$$\hat{\alpha}_{t-1}^i = \arg\min \| \hat{\alpha}_{t-1}^i \|_{\mathrm{SL0},} \ \text{s. t. } y_{t-1}^i = \Phi \Psi \alpha_{t-1}^i \quad \textbf{(9)}$$

In the formula $\alpha_{t-1}^i = [\alpha_1, \cdots, \alpha_L]^T$, ℓ_0 norm of smooth approximation SL0 norm can be expressed as: $\| \alpha_{t-1}^i \|_{\mathrm{SL0}} = L - \sum_{l=1}^{L} \exp(-\alpha_l^2 / 2\sigma^2)$. Among them, σ values used to balance the accuracy degree and smooth degree of the approximate function SL0 norm, the smaller the σ, the more similar the ℓ_0 norm.

This article through http://ee.sharif.ir/~SLzero's SL0 package optimization solution formula (9), and by $\hat{x}_{t-1}^i = \Psi \hat{\alpha}_{t-1}^i$, got high quality reconstruction reference frame.

The experiment to choose the sequence σ for $\sigma_k = \mu \sigma_{k-1} (k \geq 2)$, σ's initial value $\sigma_1 = 2 \max_l |\alpha_l|$, decline factor $\mu = 0.25$.

Non reference frame of the variable sampling rate multihypothesis re-factoring

Through the above process can under the high sampling rate of fixed gain high resolution reconstruction reference frame. Take it as the non reference frame of the variable sampling rate multihypothesis prediction re-factoring of reference, effectively improve the re-factoring quality of non reference frame.

Pretreatment of approximate constant block

At the receiving end, first determine the received the non reference frame of each block category. If it is approximate constant block y_{t,M_1}^i, then need to first through the pretreatment process. With reference frame corresponding block of measurement vector y_{t-1}^i's final $M-M_1$ values will be y_{t,M_1}^i fill long to M:

$$y_{t,M}^i = \left[(y_{t,M_1}^i)^T, y_{t-1}^i(M_1+1), \cdots, y_{t-1}^i(M) \right]^T \quad \textbf{(10)}$$

Among them, $y_{t-1}^i(j)$ shows y_{t-1}^i's the NO. j element.

Due to approximate constant block of relative reference frame corresponding blocks of the movement is very small, contain the least amount of new information, the existing M_1 measured value to represent the small difference between the two frames. At the same time, take the reference block's part of the measured values approximate as the the current of approximate constant block of measured value used, is equivalent to increase the approximate constant block of sampling rate, effectively improve the non reference frame of low sampling rate measuring's approximate constant block of reconstruction quality.

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Variable sampling rate of multihypothesis prediction

To make full use of the inter-frame correlation of video frame peculiar, this article chooses in the measurement field prediction's multihypothesis prediction method[13].

$$\hat{X}_t = \arg\min_{\hat{X}_t} \| Y_t - \Phi \hat{X}_t \|_2^2 \quad \textbf{(11)}$$

Due to be predicted signal measurement value Y_t is known, and this directly in the measurement area forecasting process to ensure the accuracy of the forecast. Notice the slowly changing block y^i_{t,M_2}'s sampling rate with other two types different (measurement vector length is M), so for the whole of the non reference frame's multihypothesis prediction process can promote for variable sampling rate of multihypothesis prediction.

Given block x^i_t, all in the reconstructed reference frame of the corresponding position of search window's image block are regarded as used to predict x^i_t of candidates block, the best linear combination of these candidate block constituted x^i_t of multihypothesis prediction, which is $\tilde{x}^i_t = H^i_t \hat{\omega}^i_t$. H^i_t shows matrix is made up of all candidate block, its column vector $h_c (c=1,\cdots,C)$ shows different candidate blocks of the vector turns, then to x^i_t's multihypothesis prediction process is to solve candidate block of the optimal linear combination coefficient $\hat{\omega}^i_t$'s process.

$$\hat{\omega}^i_t = \arg\min_{\omega} \| y^i_{t,M} - H^i_t \omega \|_2^2 \quad \textbf{(12)}$$

With Tikhonov regularization method to solve formula (12), join the penalty term for it, get it

$$\hat{\omega}^i_t = \arg\min_{\omega} \| y^i_{t,M} - \Phi H^i_t \omega \|_2^2 + \lambda \| \Gamma \omega \|_2^2 \quad \textbf{(13)}$$

λ shows Lagrangian multipliers, This paper chooses $\lambda = 0.0625$. Tikhonov matrix Γ chooses diagonal elements for $\| y^i_{t,M} - \Phi h_c \|_2$'s diagonal matrix, through this kind of structure, Γ matrix took the coefficient vector $\hat{\omega}^i_t$ implement the strategy of rewards and punishments; And the target block the more similar, the candidate block of the weighting coefficient the greater; on the contrary, the candidate block of the weighting coefficient the less. By the standard solutions formula of Tikhonov can directly get the best linear combination coefficients:

$$\hat{\omega}^i_t = ((\Phi H^i_t)^T (\Phi H^i_t) + \lambda \Gamma^T \Gamma)^{-1} (\Phi H^i_t)^T y^i_{t,M} \quad \textbf{(14)}$$

If x^i_t is slowly changing block, due to its measurement vector y^i_{t,M_2} long for M_2, using the same process for multihypothesis prediction need to use to match the measurement matrix Φ_2.

Variable sampling rate of residual re-factoring

The multihypothesis prediction obtained the prediction of the frame $\hat{X}_t$ and the original signalstill X_t there are some errors $R = X_t - \hat{X}_t$. By the linear characteristic of measurement process can be concluded that the measured value of the residual R is equal to forecast frame $\hat{X}_t$ with the original signal in the measurement domain of residual:

$$Q = \Phi R = \Phi(X_t - \hat{X}_t) = Y_t - \Phi \hat{X}_t \quad \textbf{(15)}$$

Among of them $Q \in R^{M \times K}$, Y_t shows the receiving end got measurement after preprocessing, only slowly changing block of measurement vector y^i_t long for M_2, so when $i \in I_2$ predicts residual vector q^i also only reserves before M_2 elements $q^i = \left[q_1, \cdots, q_{M_2} \right]^T$.

In this paper, by solving the minimum ℓ_1 norm optimization method of reconstructing the residual vector $r^i (i = 1, 2, \cdots, K)$, get the residual $\hat{R} = [\hat{r}^1, \hat{r}^2, \cdots, \hat{r}^K]$.

$$\hat{r}^i = \arg\min \| D^T r^i \|_1 \text{, s. t. } q^i = \Phi r^i \quad \textbf{(16)}$$

Then refactoring the non reference frame for $\hat{X}_t = \hat{X}_t + \hat{R}$. ε-Using regularization IRLS algorithm optimization solving formula (16), the objective function of ℓ_1 norm is replaced by the weighted ℓ_2 norm:

$$\hat{\gamma}^i = \arg\min \sum_{l=1}^{L} v_l \gamma_l^2 \text{, s. t. } q^i = \Phi D \gamma^i \quad \textbf{(17)}$$

Among of them, D shows the standard video test sequence's residual data by K - SVD training method of residual general dictionary, $\gamma^i = [\gamma_1, \cdots, \gamma_L]^T$ shows the residual vector r^i sparse representation coefficient under residual dictionary D, which is $\hat{r}^i = D \hat{\gamma}^i$. In the iteration solving process by the formula (17), the weighting coefficient v_l of each iteration are calculated all by the results of the previous iteration:

$$v_l = ((\gamma_l^{(k-1)})^2 + \varepsilon)^{-1/2} \quad \textbf{(18)}$$

The optimal sparse coefficient of this iteration for

$$\gamma^{(k)} = Q_k(\Phi D)^T(\Phi D Q_k(\Phi D)^T)^{-1} q^i \quad \textbf{(19)}$$

In the formula, Q_k shows this iteration of the weighting coefficient's reciprocal $1/v_l(l = 1, 2, \cdots, L)$ the composition of diagonal matrix. The literature sets the regularization factor ε initial value for 1, and with each iteration decreases ε value gradually, until the sparse coefficient converge to the optimal solution is to stop the iteration.

THE EXPERIMENTAL RESULTS

This article uses MHFP package's four groups standard video sequence to test its proposed algorithm performance: Foreman, News, Susie, Football. The package can be directly in the literature[13] author's website at http://www.ece.msstate.edu/~ewt16/publications to download. Consider test sequence before two frames, and take the NO.1 frame as the reference frame. Experiments all algorithm block size is 8×8, the sampling rate of reference frames are all fixed at 50%.

This paper's algorithm of the non reference frame of sampling rate can be according to the test sequence itself structure complicated degree and the extent of the inter-frame motion adaptive adjust size, therefore is not known in advance, but can be artificially changed parameters (all kinds of block sampling rate or classification threshold) control its probably scope of the sampling rate, to adapt to the demand of the application environment (is to reconstruct quality requirements high or to transmission data volume have large limits). The experiment of this paper by the multiple sets of video sequences is to choose a set of general strong parameters, not only ensure the sampling rate is low, and also ensuring the quality of reconstruction is higher, and in the absence of special requirements can be used as fixed parameters. Set 3 different categories of block sampling rate respectively are: $S_1 = 5\%$, $S_2 = 20\%$, $S_3 = 50\%$, Threshold of the classification decision respectively are: $T_1 = 0.003$, $T_2 = 0.15$.

Set the MHFP's search window size for ± 4 pixels. First, the experiment compared the rest of the conditions exactly the same circumstances (selection the same as MHFP of random projection matrix and the reference frame and residual reconstruction algorithm BCS-SPL-DWT) with variable sampling rate measuring method VS-MHFP1 and re-factoring structure of MHFP algorithm, as shown in TABLE 1. The analysis table's data can be seen that under the condition of the same background, just rely on variable sampling rate's measurement way can make the test sequence Foreman, News, Susie and Football's re-factoring PSNR respectively increased: 0.69 dB, 0.43 dB, 1.21 dB and 0.62 dB.

TABLE 1 : MHFP with VS-MHFP1 video frame reconstruction quality comparison (PSNR (dB))

Sequence	Sampling rate	MHFP	VS-MHFP1
Foreman	0.11	31.55	32.63
News	0.13	28.90	28.99
Susie	0.09	33.07	34.45
Football	0.25	25.79	28.23

In addition, this article proposed video compression perception reconstruction algorithm is presented V-MHFP2 and MHFP and FS-MHFP's performance comparison in TABLE 2. Among of them, FS-MHFP shows fixed sampling rate of multiple hypothesis prediction reconstruction method (besides sampling way, FS-MHFP of other terms the same as the V-MHFP2). Can be seen from the TABLE, V-MHFP2 compared with MHFP and FS-MHFP, its reconstruction quality are all improved obviously, Foreman, News, Susie, Football respectively increased: 2.67 dB, 5.55 dB, 2.52 dB, 2.95 dB, 1.29 dB, 2.70 dB, 1.76 dB, 0.64 dB. Observing and comparing Figure 2 shows the algorithm VS-MHFP2 of this paper can effectively reconstruct the main movement area of the video. In addition from the Figure 3 shows the Foreman of local amplification can also be seen in Figure for larger degree of movement around part the lips, FS-MHFP's block effect is obvious, and V-MHFP2 can effectively eliminate the block effect, improve the quality of

TABLE 2 : MHFP, FS-MHFP and V-MHFP2 video frame reconstruction quality comparison (PSNR (dB))

Sequence	Sampling rate	MHFP	FS-MHFP	VS-MHFP2
Foreman	0.12	32.25	34.25	35.12
News	0.14	30.35	33.32	36.08
Susie	0.09	35.00	35.45	37.24
Football	0.25	27.67	30.15	30.25

reconstruction.

For simpler test sequence as Susie sequence, the method of this article can reduce adaptive the total sampling rate, and can guarantee the good quality of re-factoring. For more complex test sequence as Football sequence, the method of this article can increase the adaptive sampling rate, to ensure the quality of an acceptable reconstruction. In other words, this paper proposes the variable sampling rate measurement way to select the sample rate does not need artificial judgment video complexity, it can adaptively adjust the

(a) The original frame (b) MHFP (c) FS-MHFP (d) VS-MHFP2

Figure 2 : News sequence NO.2 frame local reconstruction results (sampling rate 14%)

(a) FS-MHFP **(b) VS-MHFP2**

Figure 3 : Sampling rate for 12%, the Foreman image reconstruction results (zoom in)

size of the total sampling rate, make the system is applied in different scenarios eventually reconstruction quality is not too low.

For comparison in TABLE 1 and TABLE 2 of four kinds of algorithm complexity, in this paper, under the same experimental environment (CPU configuration: AMD Athlon(tm)II X2 255, frequency: 3.11GHz, memory: 1.75GB, running environment: MATLAB R2010a) recorded under four kinds of algorithms to deal with four video sequence in the table of the average operation time, MHFP for 7.2001s, V-MHFP1 for 7.0366s, FS-MHFP for 4.4673s, V-MHFP2 for 18.6643s. Among them, the V-MHFP1 running time and MHFP basic same, show that this article presented variable sampling rate basic thought not to increase algorithm complexity. And V-MHFP2 compared with V-MHFP1 re-factoring speed is slower, the algorithm complexity is higher, the main reason is that this article chooses the residual reconstruction algorithm IRLS is an iterative optimization solving process, reconstruction speed than taking the image for whole BCS- SPL-DWT algorithm of wavelet transform is slow.

CONCLUSION

This paper puts forward a kind of make full use of the inter-frame correlation's variable sampling rate video compression perception algorithms, for complex structure, movement larger's image block with high sampling rate is measured. In reconstructing end, the variable sampling rate multihypothesis prediction method is used to achieve the goal of make full use of the inter-frame correlation. The experimental results show that this paper proposed variable sampling rate measurement way can according to the structure and motion of different video scene adaptive adjustment of sampling rate strategy at a reasonable distribution, under the condition of total sampling rate certain make integral effect to be the optimum, improves the sampling efficiency effectively.

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