

Natural Image Super Resolution through Modified Adaptive Bilinear Interpolation Combined with Contra Harmonic Mean and Adaptive Median Filter

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Abstract—Super resolution is a technique to enhance the scale of image in digital image processing. The single low resolution and multiple low resolution techniques have been used by many researchers in reconstructing high resolution image. The above resolution increasing techniques are researched under spatial and frequency domain. When increased in the resolution of image, it is very important to retain the quality of image, which is the challenging task in the domain of digital image processing. Here in this paper, the super resolution architecture for single low resolution technique has been proposed to reconstruct the high resolution image by combining interpolation and restoration methods in spatial domain. The modified adaptive bilinear interpolation is proposed for interpolation and contra harmonic mean & adaptive median filter are used for restoration of single low resolution image. The experimentation is done on standard data set show that, the results obtained from modified adaptive bilinear interpolation are competitively improved when compare to other existing single low resolution techniques in interpolation domain.

Index Terms—Super resolution, nearest neighbor, bilinear, bicubic, modified adaptive bilinear interpolation, contra harmonic mean, adaptive median filter.

I. INTRODUCTION

The super resolution (SR) is a promising digital image processing technique to enhance the resolution of an input image. The single low resolution (SLR) and multiple low resolution (MLR) techniques have been proposed to enhance resolution of input image. The high resolution (HR) image is reconstructed either from SLR [4-6][8-10][12-14][16-21][23-30] or MLR [7][10][26] of same scene with exposed from different angles. These

techniques are explored in both spatial [2-4][9] and frequency [8] domain.

In this paper, we propose SR algorithm for SLR input image to reconstruct HR image. The modified adaptive bilinear interpolation (MABI), contra harmonic mean (CHM) and adaptive median filter (AMF) are used for interpolation and restoration of an SLR image. Initially original HR image is translated into low resolution (LR) image by using proposed interpolation technique MABI and finally the HR image is reconstructed back from SLR image by using proposed MABI, CHM & AMF techniques. Here original HR color image serves a reference image to compare the quality of approximated HR color image. The SR algorithms for SLR input image is explored through interpolation based, learning/training based and reconstruction/restoration based algorithms in spatial domain. The interpolation based methods are primarily classified under linear, nonlinear and variation methods, where in most familiar linear methods for interpolation [1-4][9][12] are nearest neighbor, bilinear, bicubic and the recent approach is to combine fuzzy logic to traditional interpolation methods. The learning/training [2][6][8][16][18-20][23][27][30] based SR is primarily focused on either building or using the prior dictionary/ knowledgebase of LR to HR mappings. Then use that dictionary/ knowledgebase to regenerate HR image. The reconstruction/ restoration based SR will primarily target on applying edge preservative [17][25][27][29], back projection [4][10][22][29] algorithms in developing HR image. Many researchers used interpolation algorithms for generating HR image, but the quality of interpolated image is decreased by using these methods. The goal of SR algorithm is in generating the HR and good visual quality image, which is predicted from a SLR input image. The effectiveness of SR algorithm depends on preciseness of the algorithm, i.e. the algorithm may decrease the image quality instead of increasing. So this paper proposes a SR algorithm which

is the hybrid version of image interpolation combined with restoration.

The remaining sections of this paper is as follows: section 2 includes the related works on enhancing resolution and restoration of an image. The section 3 explains proposed architecture with protocol phases (Interpolation and Restoration) and algorithm. The results have been discussed in the section 4 with root mean squared error (RMSE), mean squared error (MSE) and peak signal to noise ratio (PSNR) computation result statistics and finally we have summarized and concluded the paper in the section 5.

II. RELATED WORK

Major research work on SR is primarily focused on building dictionary/ knowledgebase in learning and training based SR. The [2] used learning based SR which uses adaptable k neighbours for MMSE image interpolation, where in [8] used a SLR input image and a constructed knowledgebase of LR to HR pieces using discrete wavelet transform(DWT) with inhomogeneous gaussian markov random field prior. In image hallucination [16] primal sketch priors were constructed for enhancing quality of image, a contour smoothness and reconstructive constraint is applied for construction of HR image. In patch based SR, the input LR image is divided into 3×3 patches [18] then interpolated by bicubic interpolation algorithm and matched with dictionary of patches, which hold HR image patch details for interpolated LR patch. In kernel based regression [19], the pairs of input LR to output HR example pair of input and output image were trained, training piece pair are arbitrarily selected for regression from a set of LR and corresponding desired HR image.

The sparse representation [20] for SR is based on piece wise construction, where each piece of LR input is constructed and the coefficients are used to produce HR image output by together training two databases one for LR image and other for HR image pieces. In nonnegative neighbour embedding [21] a dictionary of LR and HR trained piece group are used to understand the unknown HR details where LR feature vector in the input image is weighted group of k nearest neighbours in knowledgebase and respective HR feature vector is reconstructed. In the stastical learning [23] of SR problem with support vector machine given $N \times N$ piece from LR work is to predict 4 pixels of HR image corresponding to one center pixel. Edge focused patch based hallucination [27] is an energy function framework for finding the pieces for training set/ dictionary. When a part of input is HR in LR image [28] then SR can be constructed based on gerchberg papoulis with dynamic properties.

Most of the research of SR is on building training database, some algorithms explore on reconstruction methods for construction of HR image. In developing HR image in spatial and wavelet domain [4] the input image is interpolated using bicubic then subjected to gaussian and back projection. The back projection is one of the most striking approach for generating HR image. The

adaptive gradient magnitude self-interpolation [9] uses HR gradient calculation followed by reconstruction to generate HR image. As the iterative back projection produces jaggy effects [17], bilateral filtering with mean shift segmentation with complex shock filtering is used for generating HR image.

The recent SR technology uses wavelet transformations. The several wavelet transformation techniques has been applied to image processing to address interpolation for better edge enhancement to avoid blocking and jazzy artifacts. The interpolation based direction adaptive discrete wavelet transform (DWT) technology is used in image compression to reduce bit and scanning redundancy [31] for texture image which reduce computation cost for shrinking and reducing blocking artifacts with better effect along the edges. One of the major variation in DWT technology is the complex wavelet transform(CWT). The CWT technology uses two filter banks namely real and imaginary filter bank, so it is termed as dual tree complex wavelet transform. The CWT provides better directional selectivity compared to DWT as it decompose input image into eight sub bands out of which two are low frequency bands and six are high frequency bands. CWT with bicubic interpolation is used in image resolution enhancement of satellite images [32] and quick bird image data [33]. Other major variation in DWT technology is the stationary wavelet transform(SWT). The DWT mechanism will decompose the inputted image into four subcomponents with their size half of the input image causing loosing details along edges. The SWT will address this issue by having subcomponents with the same size as input image. The [34] is a combination of DWT and SWT technology as SWT components are fused with DWT components for edge enhancement. The [35] is a hybrid algorithm based on DWT technology and spatial domain gaussian filtering and back propagation for image resolution enhancement.

In HR image building the input LR image is to be interpolated and for that most familiar are the variations of bicubic interpolation mechanism, which uses 16 nearby pixels for generating new values for interpolated pixel. When we use bicubic the value of interpolated pixel is dependent on 16 surrounding pixel so it introduce error between actual original image and the interpolated image along edges. To reduce error we are proposing a new approach of interpolation termed MABI which uses only seven surrounding pixels. By applying MABI error between actual original image and the interpolated image are reduced and the interpolated image is then subjected to restoration for HR image reconstruction.

III. PROPOSED ARCHITECTURE

The SLR and MLR techniques have been used by many researchers in reconstructing HR image. When increases in resolution of image, it is very important to retain the quality of image at the other end is a critical task in the domain of digital image processing. So, we propose the SLR technique to reconstruct the HR image

by combining interpolation and restoration method in spatial domain. The MABI, CHM & AMF are used for interpolation and restoration of an image. The detailed flow of SR mechanism using interpolation phase and restoration phase is shown in figure 1.

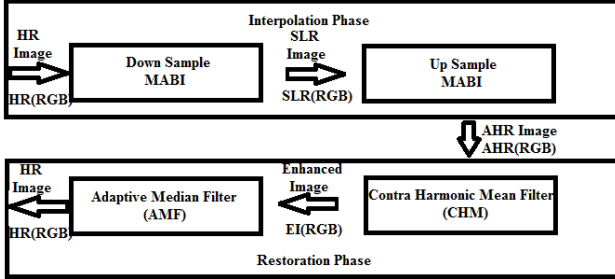


Fig.1. Proposed SR Architecture

The proposed SR architecture as shown in figure 1 accepts HR Image as input, which is also used as a reference for comparing the quality of approximated HR (AHR) image. SLR image is generated by down sampling HR image using proposed MABI interpolation function shown in figure 3 as per architecture shown in figure 4.

The SLR image is up sampled by using proposed MABI function for interpolation phase to generate AHR image. The results of MABI (AHR image with original HR) are compared with state of art interpolation algorithms nearest neighbor, bilinear and bicubic algorithms. AHR image will undergo restoration phase using CHM and AMF to regenerate HR image. The obtained results reveals a significant decreases in MSE and increases in PSNR using improved way of interpolation method MABI and the image quality for visual perception is enhanced through CHM & AMF techniques.

A. Notation

Table 1 briefs the notations used in this article for proposed SR architecture.

Table 1. Notations used in proposed architecture

Notation	Explanation
SLR(RGB)	Single low resolution colour (Red, Green, Blue) image.
IP(RGB)	Input colour image.
OP(RGB)	Output colour image.
AHR(RGB)	Approximated high resolution colour image.
EI(RGB)	Enhanced high resolution colour image.
HR(RGB)	High resolution colour image.

B. Interpolation Phase

Figure 2 depicts the protocol used in interpolation phase for the proposed architecture shown in figure 1.

The interpolation phase starts from accepting SLR(RGB) image from the user. The SLR(RGB) is interpolated by a factor of ∂ using proposed MABI function and AHR(RGB) is generated. The result of interpolation phase is subjected to restoration phase shown in figure 5.

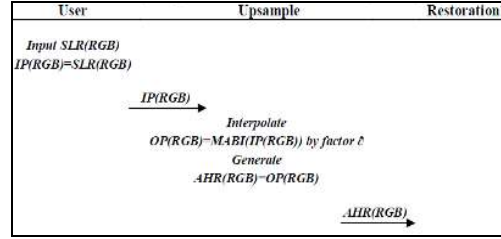


Fig.2. Protocol used in Interpolation phase

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Function MABI(IPMxN(RGB), OPcMxN(RGB))
// IPMxN(RGB) input image of size product(M,N,3)
// OPcMxN(RGB) interpolated image of size
// product(cM, cN,3) with an interpolation factor ∂.
begin
for i = 1 to ∂*M step 1
for j = 1 to ∂*N step 1
// Map interpolated pixel with (i,j) co ordinates to input
// image (x, y) co ordinates
x =  $\frac{i}{\partial}$ ; y =  $\frac{j}{\partial}$ 
//Obtain surrounding pixel (x1,y1), (x1,y2), (x2,y1) &
//(x2,y2) co-ordinates for input image (x,y) co ordinates
//using interpolated (i,j) pixel co ordinates
x1 =  $\lfloor \frac{i}{\partial} \rfloor$ ; x2 =  $\lfloor \frac{i}{\partial} \rfloor + 1$ ; y1 =  $\lfloor \frac{j}{\partial} \rfloor$ ; y2 =  $\lfloor \frac{j}{\partial} \rfloor + 1$ 
//Apply bilinear interpolation on input image pixel
// values, r1 represent interpolation along x1 axis and
//r2 represent interpolation along x2 axis of figure 4
//and final result in stored in Result1x,y(RGB)
r1 = IPx1,y1(RGB) +  $\frac{(y - y_1)}{(y_2 - y_1)} * (IP_{x_1,y_2}(RGB) - IP_{x_1,y_1}(RGB))$ 
r2 = IPx2,y1(RGB) +  $\frac{(y - y_1)}{(y_2 - y_1)} * (IP_{x_2,y_2}(RGB) - IP_{x_2,y_1}(RGB))$ 
Result1x,y(RGB) = r1 +  $\frac{(x - x_1)}{(x_2 - x_1)} * (r_2 - r_1)$ 
//Alter any one of the surrounding pixel values based on
//Euclidian distance (x,y) with (x1,y1), (x1,y2), (x2,y1) &
//(x2,y2) with their neighbors as shown in figure 4.
x0=x-1; y0=y-1; x3=x+1; y3=y+1;
if(x<x1 and y<y1)
IPx1,y1(RGB) =  $\frac{\sum_{p=0,1} \sum_{q=0,1} IP_{x_p,y_q}(RGB)}{4}$ 
if(x<x1 and y<y2)
IPx1,y2(RGB) =  $\frac{\sum_{p=0,1} \sum_{q=2,3} IP_{x_p,y_q}(RGB)}{4}$ 
if(x<x2 and y<y1)
IPx2,y1(RGB) =  $\frac{\sum_{p=2,3} \sum_{q=0,1} IP_{x_p,y_q}(RGB)}{4}$ 
if(x<x2 and y<y2)
IPx2,y2(RGB) =  $\frac{\sum_{p=2,3} \sum_{q=2,3} IP_{x_p,y_q}(RGB)}{4}$ 
//Apply bilinear interpolation on altered surrounding
// pixel values and store result in Result2x,y(RGB)
r1 = IPx1,y1(RGB) +  $\frac{(y - y_1)}{(y_2 - y_1)} * (IP_{x_1,y_2}(RGB) - IP_{x_1,y_1}(RGB))$ 
r2 = IPx2,y1(RGB) +  $\frac{(y - y_1)}{(y_2 - y_1)} * (IP_{x_2,y_2}(RGB) - IP_{x_2,y_1}(RGB))$ 
Result2x,y(RGB) = r1 +  $\frac{(x - x_1)}{(x_2 - x_1)} * (r_2 - r_1)$ 
//Fuse the results with max filter and store at
//interpolated pixel (i,j) co ordinates of output image
OPi,j(RGB) = max(Result1x,y(RGB), Result2x,y(RGB))
end for
end for
end
    
```

Fig.3. Function MABI

The image interpolation function ranging from nearest neighbor to bicubic suffers from blurring edges and losing image details, So in order to improve interpolation mechanism MABI is proposed. The figure 3 shows the implementation details for MABI architecture shown in figure 4, which not only interpolates the input image but also increases smoothness using smoothing kernel.

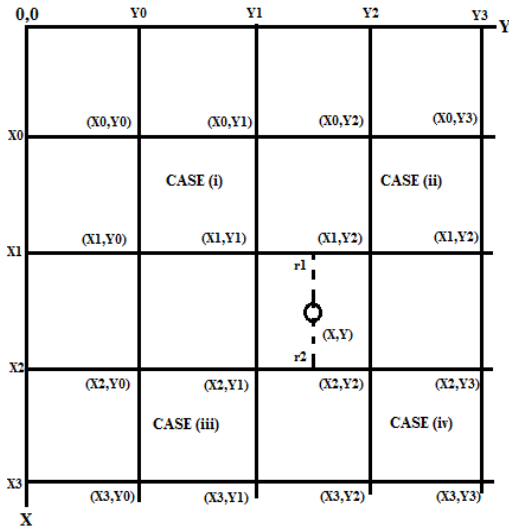


Fig.4. MABI Architecture

C. Restoration Phase

Figure 5 shows the protocol used in restoration phase for the proposed architecture shown in figure 1. The restoration phase is done in two levels restoration 1 and restoration 2. Restoration 1 accepts AHR(RGB) generated from interpolation phase shown in figure 2 and uses CHM filter, which reduces jaggy effect in generated AHR(RGB) using a smoothing kernel of order Q. The result of restoration1 is EI(RGB) is feed into restoration 2 level. The restoration 2 uses AMF to generate HR(RGB). AMF is a local filter works based on non linear median filtering, which produces better results [1] than other linear filtering mechanisms. The generated HR(RGB) is visually pleasant HR image generated from SLR image using SR mechanism.

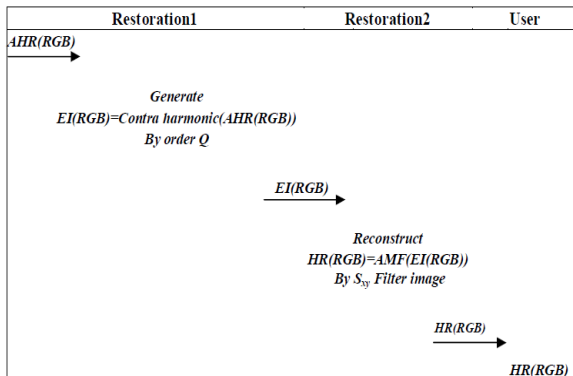


Fig.5. Protocol used in restoration phase

The AHR(RGB) image of MABI is subjected to CHM kernel [1][4] as shown in equation (1), which is used as smoothing kernel in spatial domain.

$$EI(RGB) = \frac{\sum_{(st) \in S_{xy}} AHR(RGB) (st)^{Q+1}}{\sum_{(st) \in S_{xy}} AHR(RGB) (st)^Q} \quad (1)$$

Where

AHR(RGB) -> MABI interpolated RGB image.

Q -> Order of the filter.

EI(RGB) -> Enhanced RGB image obtained after contra harmonic mean filtering.

The EI(RGB) image is subjected to AMF [1] algorithm shown in figure 6. AMF is a non linear filter to significantly reduce irregularities in generated image and sharpen the EI(RGB) image which is termed as SR image.

```

Algorithm AMF( EI( RGB ), OP( RGB ) )
// EI( RGB ) input image of size product( OM,
OM, 3 )
// SR( RGB ) SR image of size product( OM,
OM, 3 ).
begin
Stage A:
Value1 = EI( RGB )_med - EI( RGB )_min
Value2 = EI( RGB )_med - EI( RGB )_max
If ( Value1 > 0 ) and ( Value2 < 0 ) go to stage B
Else increase the window size
If window size ≤ S_max repeat Stage A
Else output SR( RGB ) = EI( RGB )_med
Stage B:
Value3 = EI( RGB )_xy - EI( RGB )_min
Value4 = EI( RGB )_xy - EI( RGB )_max
If ( Value3 > 0 ) and ( Value4 < 0 ),
output SR( RGB ) = EI( RGB )_xy
Else output SR( RGB ) = EI( RGB )_med
end
Where
EI( RGB )_min: Minimum intensity value of S_xy
EI( RGB )_max: Maximum intensity value of S_xy
EI( RGB )_med: Median intensity value S_xy
EI( RGB )_xy : Intensity values at coordinates ( x, y )
S_xy: Filter image
S_max: Maximum allowed size of S_xy

```

Fig.6. Algorithm for adaptive median filter

IV. RESULTS AND DISCUSSION

The first part of our SR algorithm involves interpolation. The set of input images shown in figure 7 are considered for experimentation on proposed MABI, nearest neighbor, bilinear and bicubic interpolation in MATLAB. The input images are referred from standard MATLAB data set.



(i) Lena
Size:256X256X3



(ii): Lena
Size: 512X512X3



(iii): onion.png
Size: 135X198X3



(iv): pears.png
Size: 486X732X3



(v): west.png
Size: 394X369X3

Fig.7. Set of input images

The obtained results for figure 7 case (i) input image are shown in figure 8 and are compared with original image using RMSE, MSE and PSNR and tabulated in table 2. There is drastic decrease in RMSE, MSE and significant increase in PSNR. Which shows that our method of interpolation MABI calculate near to original image better than other techniques and competent to result of learning/training based SR algorithms.



(a) Nearest neighbor



(b)Bilinear



(c)Bicubic



(d) MABI

Fig.8. Interpolation of input image(i) from figure 7.

When same experiment was repeated by first down sampling by nearest neighbour, bilinear, bicubic and MABI approach by 0.5 for all input images of figure 7 and then up sampling by nearest neighbour, bilinear, bicubic and MABI approach by 2.0 respectively. The result statistics for each input image is compared with interpolated image and obtained RMSE, MSE & PSNR values for each is shown in table 2 and performance analysed through figure 9,10 and 11 respectively.

Table 2. RMSE, MSE and PSNR Computation statistics

Image	RMSE Tabulation			
	Nearest Neighbor	Bilinear	Bicubic	MABI
Lena 256X256X3	5.2128	4.8560	4.4997	3.5684
Lena 512X512X3	4.9409	4.3062	4.1357	3.3934
onion.png 135X198X3	4.9053	4.5358	4.2778	3.2784
pears.png 486X732X3	3.7416	2.9790	2.8964	2.2744
west.png 394X369X3	6.4076	6.0621	5.4526	4.4604
Image	MSE Tabulation			
	Nearest Neighbor	Bilinear	Bicubic	MABI
Lena 256X256X3	27.1740	23.5810	20.2475	12.7337
Lena 512X512X3	24.4127	18.5439	17.1043	11.5153
onion.png 135X198X3	24.0626	20.5733	18.2995	10.7482
pears.png 486X732X3	13.9997	8.8744	8.3893	5.1730
west.png 394X369X3	41.0571	36.7493	29.7307	19.8952
Image	PSNR Tabulation			
	Nearest Neighbor	Bilinear	Bicubic	MABI
Lena 256X256X3	33.7893	34.4052	35.0671	37.0813
Lena 512X512X3	34.2546	35.4488	35.7997	37.5180
onion.png 135X198X3	34.3174	34.9978	35.5064	37.8174
pears.png 486X732X3	36.6696	38.6494	38.8935	40.9934
west.png 394X369X3	31.9969	32.4783	33.3988	35.1433

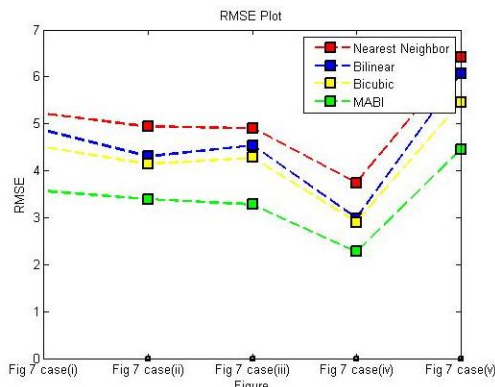


Fig.9. RMSE Performance of different interpolation methods for SR evaluated as per table 2 RMSE tabulation cost

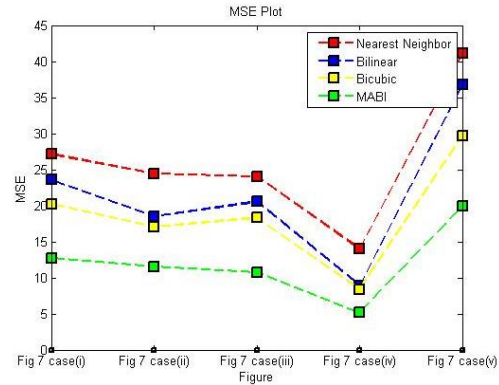


Fig.10. MSE Performance of different interpolation methods for SR evaluated as per table 2 MSE tabulation cost

The RMSE performance of figure 9 and MSE performance of figure 10 reveals designed MABI function approximates SLR to approximated HR, which very closely resembles original HR. The error rate between state of art algorithm is very less.

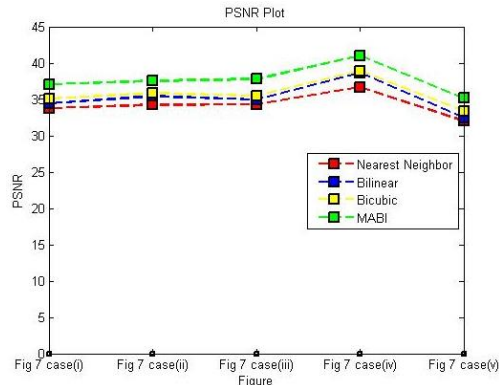


Fig.11. PSNR Performance of different interpolation methods for SR evaluated as per table 2 MSE tabulation cost measured in dB

The analysis of figure 11 PSNR performance shows approximated signal rate is high than noise compared to other interpolation algorithms. The study of figure 9, 10 and 11 shows MABI interpolates more accurately than other interpolation techniques for super resolution in SLR interpolation domain.

The CHM kernel is applied on proposed MABI resultant image obtained in figure 8 (d) for increasing psycho visual effect. The result of CHM is sharpened using AMF to remove blurriness and introduce smoothness at edge transitions as shown in figure 12.



Fig.12. Reconstruction from the interpolated image

V. CONCLUSION

In this paper, we have designed and implemented MABI algorithm and tested on several color images. The obtained results are compared with the current interpolation algorithms in spatial domain for single color image SR. The proposed algorithm is useful for creating HR colour image. The study of this algorithm put conclusion that interpolation algorithms in spatial domain will not exactly approximate along edges. Restoration mechanisms are needed for increasing accuracy on edges, which is done using CHM and AMF mechanisms. Competitive result statistics shows the potential of our MABI algorithm.

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