AN ADAPTIVE CHROMOSOME BASED COST AGGREGATION APPROACH FOR DEVELOPING A HIGH QUALITY STEREO VISION MODEL

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Abstract: *Stereo vision has traditionally been and continues to be one of the most extensively investigated topics in computer vision. Since stereo can provide depth information, it has potential uses in many visual domains such as autonomous navigation, 3D reconstruction, object recognition and surveillance systems. At present, few high-performance implementations of stereo vision algorithms exist. The key challenge in realizing a reliable embedded real-time stereo vision system is keeping the balance of execution time and the quality of the matching results. In this paper we have designed a real-time stereo vision model based on adaptive chromosome aggregation approach. When performing cost aggregation, the support from an adjacent pixel is valid only if such pixel has same variation. The way to choose proper support is a key factor of the correlation technique. For this purpose, an adaptive support weight (AW) algorithm is proposed to carry out aggregation on the appropriate support. This adaptive support weight approach begins from an edge-preserving image smoothing method called bilateral filtering. It unites gray levels or colors based on both their geometric closeness and their photometric similarity and prefers near values to remote values in both domain and range. The final disparity selection in our proposed method is performed with the help of the genetic algorithm which is an optimization technique that helps to select the best disparity value for further processing and results proved that our method is very efficient with 80% of bad pixel error reduction compared with other state of art algorithms and it attains 49% of PSNR .*

Keywords: *Adaptive support weight; matching cost; mutation; crossover; cost aggregation*

1. INTRODUCTION

Real-Time systems span several domains of computer science. They are defense and space systems, networked multimedia systems, embedded automotive electronics etc. In a real-time system the correctness of the system behavior depends not only the logical results of the computations, but also on the physical instant at which these results are produced. A real-time system changes its state as a function of physical time, e.g., a chemical reaction continues to change its state even after its controlling computer system has stopped. Real-Time systems can be classified from different perspectives. The first two classifications, hard real-time versus soft real-time, and fail-safe versus fail-operational, depend on the characteristics of the application, i.e., on factors outside the computer system. The second three classifications, guaranteed-timeliness versus best-effort, resource-adequate versus resource-inadequate, and event-triggered versus time-triggered, depend on the design and implementation, i.e., on factors inside the computer system.

The lifeblood of today's real-time embedded computer systems is the steady stream of new technology and components. These include transducer interfaces, processors, network interfaces, memory devices, state machines, high-capacity storage devices, DSP engines, timing and synchronization components, parallel digital interfaces, high-speed data links and standard bus interfaces. As soon as new devices become available, system integrators look for them on board-level products so they can compete more effectively with that new technology. But these devices use high-density packaging that mandates sophisticated electrical, mechanical and thermal design, as well as complex assembly and test procedures in manufacturing. All this leads to longer development cycles, a trend directly at odds with increasingly shorter product life cycles! Because they are reconfigurable, FPGAs not only support many of the key resources on these boards, but also help extend product life cycles. A field-programmable gate array (FPGA) is an integrated circuit designed to be configured by a customer or a designer after manufacturing, hence "field-programmable". The FPGA configuration is generally specified using a hardware description language (HDL), similar to that used for an application-specific integrated circuit

(ASIC). As FPGAs continue to evolve, the devices have become more integrated. Hard intellectual property (IP) blocks built into the FPGA fabric provide rich functions while lowering power and cost and freeing up logic resources for product differentiation. Newer FPGA families are being developed with hard embedded processors, transforming the devices into systems on a chip (SoC).

Compared to ASICs or ASSPs, FPGAs offer many design advantages, including:

- Rapid prototyping
- Shorter time to market
- The ability to re-program in the field for debugging
- Lower NRE costs
- Long product life cycle to mitigate obsolescence risk

Stereo vision is a popular technique for maintaining three-dimensional images in robotic applications. It is flexible, small in size and since it is entirely passive, it does not affect its neighborhood. Stereo vision uses two cameras side by side, measuring the displacement of the image objects caused by the cameras' different viewpoints [1].Real time performance of approximately 30 frames per second is mandatory and a very critical design issue. Embedded stereo vision sensors, consisting of a sensor head and a calculation unit, are very well suited for stereoscopic perception, but require huge computational effort. Due to mounting tolerances within the sensor head, resulting in a maximum relative shift and revolution of these two camera images, rectification is absolutely necessary to reduce the matching effort [2].

Stereo vision systems determine depth from two or more images which are taken at the same time, but from slightly different viewpoints. The most important and time consuming task for a stereo vision system is the registration of both images, i.e. the identification of corresponding pixels. Area-based stereo attempts to determine the correspondence for every pixel, which results in a dense depth map. Correlation is the basic method to find corresponding pixels [3]. Several real time systems have been developed using correlation-based stereo. However, correlation assumes that the depth is equal for all pixels of a correlation window. This assumption is violated at depth discontinuities. The result is that object borders are blurred and small details or objects are removed, depending on the size of the correlation window. Small correlation windows reduce the problem, but increase the influence of noise, which leads to a decrease of correct matches [4].

Recent advances in hardware have allowed vision researchers to develop real-time stereo vision systems. Real-time Stereo Vision system can be applied for Head Pose and Gaze Direction Measurement [5], Mobile Robot Navigation [6] and many more. Vision systems are light weight; compact, relatively inexpensive and can provide high resolution images for localization as well as mapping at a fairly high frequency[7].

Many vision algorithms have been implemented on FPGAs: not only local operations but global operations such as 2D discrete cosine transform, image restoration based on convolution, and Hough transform using CORDIC. This suggests that the system can realize local and global operations by implementing them on an FPGA [8].

The rest of the paper is organized as follows. Section II explains the researches that are related to our proposed method. Section III shows our proposed model for developing an efficient stereo vision system based on adaptive cost aggregation approach. Section IV explains the result of the proposed methodology and finally Section V concludes the method with suggestions for future works.

2. RELATED RESEARCH

Stereo vision systems take advantage of the fact that the depth of the objects in the scene can be inferred from the relative displacements, also called disparities, of the objects in the scene, when observed from two viewpoints, separated by a distance. It is one of the most heavily investigated areas of research in the field of computer vision. Some of the recent researches about real time systems and stereo vision systems are given in this section.

Real-time stereo vision was a very resource intensive application, requiring a high computational performance. Kristian Ambrosch *et al*. [1] analyzed the well known Census Transform not only for an increase in accuracy, but also for a reduction in complexity. They have proposed a novel approach, using the Modified Census Transform on the intensity as well as the gradient images that can be efficiently combined with a sparse computation. Their evaluation of that approach on the images of the Middlebury stereo ranking shows that it allows scaling the algorithm's complexity down by a factor of 5.8, while still being more accurate than the original transforms.

Leonardo De-Maeztu *et al*. [2] presented a new solution which is based on the computational simplicity of anisotropic diffusion algorithms at increased the efficiency of the aggregation process and avoiding additional computations of Adaptive-weight algorithms.

Stereoscopic 3D reconstruction is an important algorithm in the field of Computer Vision, with a variety of applications in embedded and real-time systems. Patrik kamencay *et al*. [9] presented hybrid segmentation based stereo matching method which combine Belief Propagation and Mean Shift algorithms with aim to refine the disparity and depth map by using a stereo pair of images. This algorithm utilizes image filtering and modified SAD (Sum of Absolute Differences) stereo matching method for achieving high confidence disparity. The phase based depth estimation is discussed by Javier Diaz *et al*. [10] which is simple and fast technique . His proposed technique avoids the problem of phase warping and was much less susceptible to camera noise and distortion than standard block-matching stereo systems.

Haixu Liu *et al*. [11] described a novel local-based algorithm for stereo matching using Gabor-Feature-Image and Confidence-Mask. He developed a new cost function based on Gabor-Feature-Image for obtaining a more accurate matching cost volume. Furthermore, in order to eliminate the matching ambiguities brought by the winner takes- all method, an effective disparity refinement strategy using Confidence-Mask is implemented to select and refine the less reliable pixels.

Chhatrala Nayankumar D. et al [12] described Stereo vision systems aiming at reconstructing 3D scenes. He proposed the hybrid algorithm based on k-means segmentation and refine the disparity map of the stereo image by SSD (sum of squared difference) and 3D view can also be generated by using Disparity Map and Depth Map.

J.J. Lee *et al*. [13] introduced a neural network model of stereoscopic vision, in which a process of fusion seeks the correspondence between points of stereo inputs. In this model, some matches in stereo vision correspondence are found by self-organization. But in order to increase the properties of self-organization of such a network, it would be interesting to find a way to still generate internal supervisory signals when disparity gradients are present in the inputs, so that such inputs could be learned.

Zucheul Lee *et al*.[14] described the classical local disparity methods utilize additional processing steps such as iteration, segmentation, calibration and propagation, similar to global methods. He presented an efficient one-pass local method with no iteration. In this local method, for the accuracy of similarity measure, a novel three- mode cross census transform with a noise buffer is used , which increases the robustness to image noise in flat areas. It is also used to improve the reliability of the aggregation by adopting the advanced support weight and incorporating motion flow to achieve better depth map near edges.

Doaa A. Altantawy *et al*. [15] proposed a new hybrid local-global stereo matching algorithm which is a new energy formulation of the stereo problem in segment domain. Globally and locally a new gradient mask is used for similarity measure and bilateral filter, with its edge preserving sense, is adopted for more proper disparity assignment. The experimental results on the Middlebury dataset demonstrate that this approach stands as a strong candidate with the modern stereo matching algorithms.

Real-time stereo vision systems have many applications from autonomous navigation for vehicles through surveillance to materials handling. Accurate scene interpretation depends on ability to process high resolution images in real-time, but, although the calculations for stereo matching were basically simple, a practical system needs to evaluate at least 109 disparities every second - beyond the capability of a single processor. Stereo correspondence algorithms have high degrees of inherent parallelism and are thus good candidates for parallel implementations.

A. Arranz et al[16] proposed a genetic based paper, in which a new crossover and a mutation operator is introduced which accounts for occlusion management and a new fitness function which considers occluded pixels and photometric derivatives.

Both left and right disparity images are analyzed in order to classify occluded pixels correctly. The proposed fitness function is compared to the traditional energy function based in the framework of the Markov Random Fields. The results show that a 32% bad-pixel error reduction can be achieved on average using the proposed fitness function.

3. PROPOSED MODEL FOR DEVELOPING AN EFFICIENT STEREO VISION SYSTEM

In this section, the mathematical modelling of WECS based DFIG system and its controllers are briefly discussed. The mathematical modelling of WECS is given as follows,

3.1 Stereo vision System

Stereo vision systems determine depth from two or more images which are taken at the same time, but from slightly different viewpoints. The most important and time consuming task for a stereo vision system is the registration of both images, i.e. the identification of corresponding pixels. Stereo vision systems take advantage of the fact that the depth of the objects in the scene can be inferred from the relative displacements, also called disparities, of the objects in the scene, when observed from two viewpoints, separated by a distance. In our proposed method the entire stereo vision system is designed and implemented based on adaptive cost aggregation method.

3.2 Adaptive Cost Aggregation Method

In local algorithms, the vagueness is diminished by aggregating matching costs over a correlation window. The correlation window represents local support region implicitly implies that the depth is identical for all pixels inside. And this intrinsic assumption will cause many errors particularly at the region of depth discontinuities [17]. When performing cost aggregation, the support from an adjacent pixel is valid only if such pixel has same variation. The way to choose proper support is a key factor of the correlation technique. For this purpose, in our proposed method we utilized an adaptive support weight (AW) algorithm to carry out aggregation on the appropriate support [18].There are different steps involved in our proposed method as shown in Fig.1

3.3 Process involved in Adaptive Cost Aggregation Method

The adaptive cost aggregation method for stereo matching is performed with the help of Adaptive support weight Algorithm in our proposed method. The adaptive support weight algorithm mainly concentrates on a suitable support window which is selected for each pixel in order to provide reliable and certain measurement. The adaptive support-weight of a particular pixel is measured depending on the photometric and geometric relationship with the pixel which is being considered.

This adaptive support weight approach begins from an edge-preserving image smoothing method called bilateral filtering. It unites gray levels or colors based on both their geometric closeness and their photometric similarity, and prefers near values to remote values in both domain and range. The various steps that are carried out in the Adaptive support weight Algorithm is given in the following sections.

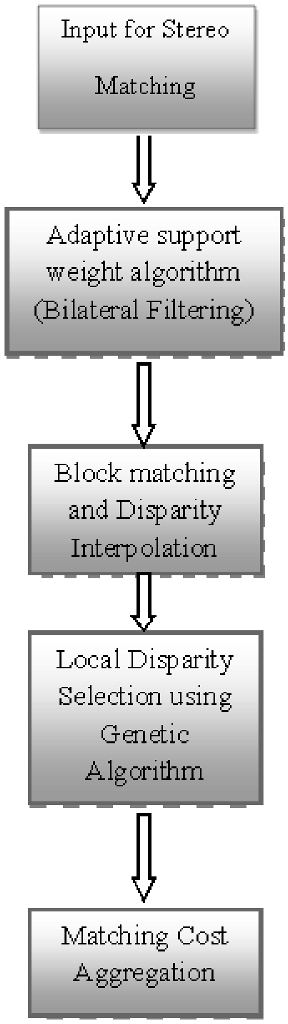


Fig. 1 Steps involved in Adaptive Cost Aggregation method

3.3.1 Bilateral Filtering

In bilateral filter, the weight range W_r is taken as the function of variations between pairs of connected pixels. The single difference can be utilized for measuring the similarity of related two pixels. Along with the difference of pixels, the neighborhood information should be included in range weight computation. For this the bilateral filter is modified and range weight is computed based on patch similarity around two connected pixels.

The Range distance D_r is given as ,

$$D_r(a_m, a_n) = \frac{\sum_i H_\sigma(i) z(a_{m+i}, a_{n+i)})}{\sum_m H_\sigma(i)} \quad (1)$$

where,

$\sum_i H_\sigma(i)$ is the normalization coefficient for the entire applied weight, $z(a_{m+i}, a_{n+i)})$ is the range of corresponding pixels.

a_{m+i}, a_{n+i} are the neighbors of a_m, a_n respectively.

The range weight of the process is computed using the formula in equation (2) ,

$$W_r(a_m, a_n) = \exp\left(\frac{-D_r(a_m, a_n)}{2\sigma} \right) \quad (2)$$

where $W_r(a_m, a_n)$ is the Gaussian function of pixel position a_m, a_n and σ is standard deviation. The equation (2) can be modified for calculating the weight of the neighbors which is given in equation (3)

$$W_{r2}(a_m, a_n) = \frac{\sum_s H_\omega(s) W_{r1}(a_{m+s}, a_{n+s)})}{\sum_s H_\omega(s)} \quad (3)$$

Using these equations, the bilateral filtering is performed in the pixels and it is followed by the next step in our aggregation model.

3.3.2 Matching cost computation

For matching the cost computation we use for absolute difference between the left and the right pixel intensity value which is obtained from the filtering. This can be calculated using the following expression,

$$|f(a,b) - g(a+l, b)| \quad (4)$$

where *l* is the disparity value. Generally the pixels in the left and right view must have the similar intensity values with matching cost of zero. For every pixel $f(a,b)$ in the reference image the matching cost is calculated using the expression (4) .Finally we get the cost value *C,* which is in relation with *a, b and l.*

3.3.3 Local Disparity Selection

Dynamic Programming is a commonly used method in stereo vision system because of its optimized results and low computational complexity. The matching cost volume for $C\ (a,b,l)$ as per equation (4) can be compared with that of the data term and the smoothing term which is as shown in (5) ,

$$D(k) = D_d(k) + D_s(k) \quad (5)$$

Here, $D_d(k)$ is the data term that is referred to as the matching cost and $D_s(k)$ is the smoothness value for encoding the assumption of smoothing. The expression for the smoothness can be expressed as shown in (6),

$$D_s(k) = \alpha \sum_a |k(a) - k(a+1)| \quad (6)$$

DP can handle the disparity problem using the optimal substructure by combining the solutions with the sub-problems. The disparity selection in our proposed method is performed with the help of the Genetic algorithm which is an optimization technique that helps to select the best disparity value for further processing and is better than dynamic programming.

3.3.3.1 Genetic Algorithm for the proposed Disparity selection

In Genetic algorithm, initially chromosomes are generated in which genes are the indices of the database images. These genes are generated without any repetition within the chromosome and the chromosomes are subjected to the genetic operators, crossover and mutation, and hence the new chromosomes are generated. Then the fitness is determined for the newly generated chromosomes. The various steps involved in the proposed GA is given Fig 2

i) Generation of Chromosomes

Initially generate N_s number of random chromosomes. The number of genes in each chromosome rely on the number of images required which are most similar to the given query image. As discussed earlier, the generated genes are the indices of the database images,

$$H^{(j)} = \{H_0^{(j)}, H_2^{(j)}, H_3^{(j)}, \cdots, H_{n-1}^{(j)}\} \ 0 \le j \le N \ -1 \ , \ 0 \le m \le n-1 \quad (7)$$

n - Number of similar images to be retrieved

In equation (7) , $H_m^{(j)}$ represents the m^{th} gene of the j^{th} chromosome. The disparity values are selected and for each of this disparity the fitness value is calculated and based on these fitness values, further processing of GA are carried out.

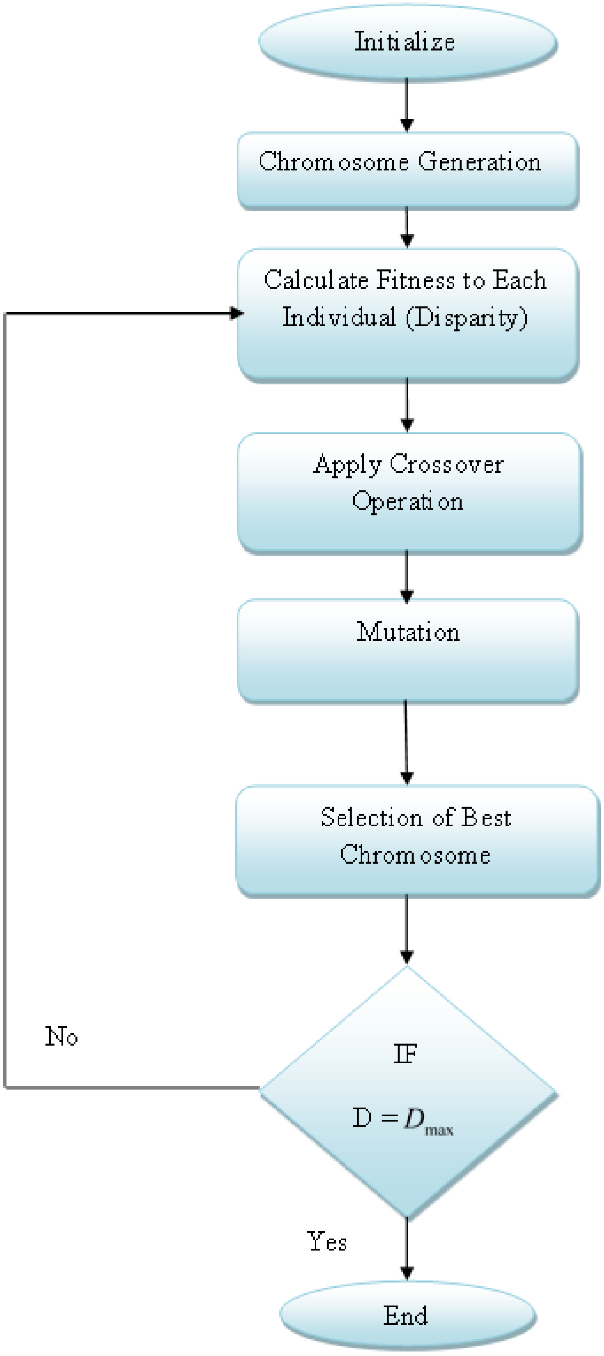


Fig. 2 Various steps involved in our Genetic Algorithm.

ii) Fitness Function

Evaluate fitness function (it will give best input that will satisfy the best or actual solution). Higher fitness function means better solution. Following are the purpose of fitness function.

- The fitness function is used for Parent selection
- Fitness function measure for convergence
- For Steady state: Selection of individuals to die
- Should reflect the value of the chromosome in some “real” way

Fitness function is a type of objective function, which is the leading target parameter to the optimized value. The fitness function is calculated by using the following formula.

$$F_j^1 = \sum_{j=0}^{N} ((C_j + W_j)/2)$$

$$\mathrm{F}_j^2 = \sum_{j=0}^{N} ((C1_j + W1_j)/2) \tag{8}$$

$$\mathrm{F}_t = F_j^1 + F_j^2$$

Here the fitness value of each chromosome is calculated based on the coverage and weight of the genes.

iii) Crossover and Mutation

Among different types of crossovers, the two point crossover is selected. In the two point crossover, two points are selected on the parent chromosomes using the equations (9) & (10). The genes in between the two points c_1 and c_2 are interchanged between the parent chromosomes and so $N/2$ children chromosomes are obtained. The crossover points c_1 and c_2 are determined as follows

$$c_1 = \frac{|H_m^{(j)}|}{3} \tag{9}$$

$$c_2 = c_1 + \frac{|H_m^{(j)}|}{2} \tag{10}$$

Now, we have the children chromosomes stored separately and their corresponding indices from $H_m^{(j)}$ stored in $H_{new\,m}^{(j)}$. Then, the mutation is accomplished by replacing N_M number of genes from every chromosome with new genes. The replaced genes are the randomly generated genes without any repetition within the chromosome. Then, chromosomes which are selected for crossover operation, and the chromosomes which are obtained from the mutation are combined, and so the population pool is filled up with the N chromosomes. Then, the process is repeated iteratively until it reaches a maximum iteration of $I_{\max}$. The final step is the convergence process where it decides when to stop. Convergence step can be defined previously at a given threshold or maximum iteration can be calculated when above steps repeat the same value

iv) Selection of Optimal Solution

After the process is repeated $I_{\max}$ times, best chromosomes are selected from the obtained group of chromosomes. Here, the best chromosomes are the chromosomes which have maximum fitness. The obtained best chromosome is used to retrieve similar images from the database. In other words, the database images that are represented by the indices, which are obtained from the genes of the best chromosomes, are the images similar to the given query image and they are retrieved in an effective manner. Even though a number of selection methods are in GA, we used Roulette-Wheel Selection.

Roulette-Wheel Selection

The quality of solution depends on the choice of the selection method. The role of Roulette-Wheel is the area covered by the entire chromosome in a population as per the fitness value. Every individual gives the slice of Roulette-Wheel and the sizes of slice are directly proportional to the each individual fitness. The main reason for choosing roulette wheel selection is that it discards none of the individuals in the population and gives a chance to all of them to be selected. Therefore, diversity in the population is preserved and when implementing in parallel, it has efficient time complexity.

The *j*th string in the population is chosen with a probability proportional to f_j. The probability for selecting the *j*th string is

$$p_j = \frac{f_j}{\sum_{j=1}^{n} f_j} \qquad (11)$$

where n is the population size.

The average fitness of the population is calculated as

$$f = \sum_{j=1}^{n} f_j \qquad (12)$$

Here we will check our constraints are satisfied or not. If constraints are satisfied then we will select this output.

The general flow graph of genetic algorithm is shown in Fig 3. It consists of three important steps such as production, evaluation, and verification. In the production step, more suitable chromosomes are produced from the previous population using chromosome crossover and gene mutation until the gene pool is filled. The initial population of the gene pool can be randomly or intentionally generated. Next, when the pool has filled out, all the chromosomes are evaluated by a fitness function and a fitness value is assigned to each chromosome according to its fitness. After the fitness allotment, the natural selection is executed.

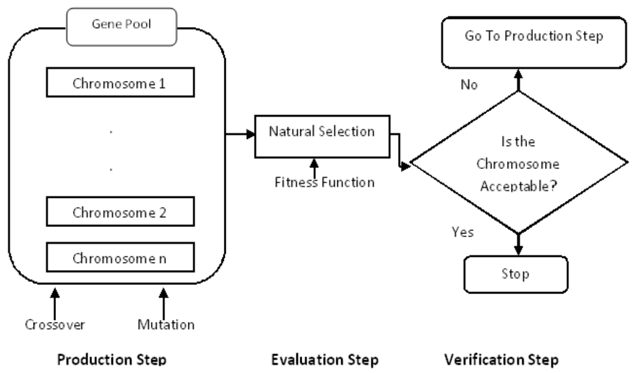


Fig. 3 Flow diagram of Genetic Algorithm

3.3.4 Matching cost Aggregation

The matching cost Aggregation is the major step involved in our Adaptive cost aggregation approach. In a stereo vision system, the major cost of the process is calculated using the expression given in (13) ,

$$C_1(a,b,l) = \sum_{(x_1,y_1)\in\mu} C(x_1, y_1, l) \qquad (13)$$

where μ is the neighbor value around $f(a,b)$. If the surface is considered to be smooth, then the pixel value of the neighbors is considered to have the same disparity value. Given a pixel value *t* and a pixel *h* in its support region, the matching cost from the support region pixel *h* is weighted based on the color difference between these two pixels *t* and *h*, along with the Euclidian distance between these two pixels

t and h on the image plane. The expression for the weight is given in the equation (14)

$$W(t,h) = \exp\left(-\left(\frac{\Delta C_{th}}{\lambda}\right) - \left(\frac{\Delta E_{th}}{\varphi}\right)\right) \qquad (14)$$

Where ΔC_{th} is the color difference between two pixels t and h, ΔE_{th} is the Euclidian distance between these two pixels t and h, λ and φ are the weighting constants respectively.

The aggregated cost is the sum of weighted cost per each pixel and it is represented as given in equation (15),

$$C_a(a,b) = \frac{\sum_{h \in \mu_t, h_1 \in \mu_g} W(t,h) W_1(g,h_1) C(a,b)}{\sum_{h \in \mu_t, h_1 \in \mu_g} W(t,h) W_1(g,h_1)} \qquad (15)$$

$W_1(g,h_1)$ - Pixel weight from disparity image

Using the equation (15) the cost aggregation of the pixels is calculated which helps in developing an efficient stereo vision system.

4. RESULTS AND DISCUSSION

The proposed method for cost aggregation for high quality stereo matching is implemented in the working platform of MATLAB (version 7.12.0). The recognition process is tested with stereo images and the obtained result of the proposed work has been shown in Fig 4. Initially, the stereo images are separated into left and right image and then processing like matching cost aggregation, disparity computation, and disparity selection are performed for each of these images and the cost aggregation is finally obtained. The results obtained by our proposed method is shown in Fig. 4

Fig (a) Right and Left Stereo images

The Fig 4 shows the stereo matching process for 'TEDDY' image. Fig 4 (a) is the input stereo right and left images which is to be processed. Fig 4(b) is the filtered output of the right and left image and 4(c) is ground truth image. The filtering performed in our proposed method is bilateral filtering. Once the images separated from the noise using filtering method, the disparity map is obtained for the image. Fig 4(d) shows the image after the after disparity selection and the Fig (e) shows the stereo image. The Fig 4 (f) is the final stereo matched output image obtained by our proposed method. The above process is repeated for different Middlebury data and there results are shown in Fig 5. The Cost aggregation, RMS and the PSNR values for the different images while processing are calculated and is given in the below table (1) and comparison values are given in table (2).

Fig (b) Right and Left images after bilateral filtering.

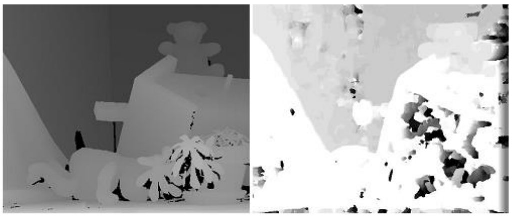


Fig (c) Ground Truth Image Fig (d) Disparity image

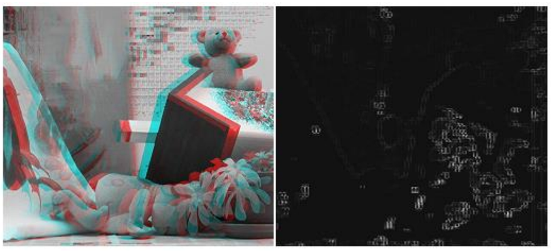
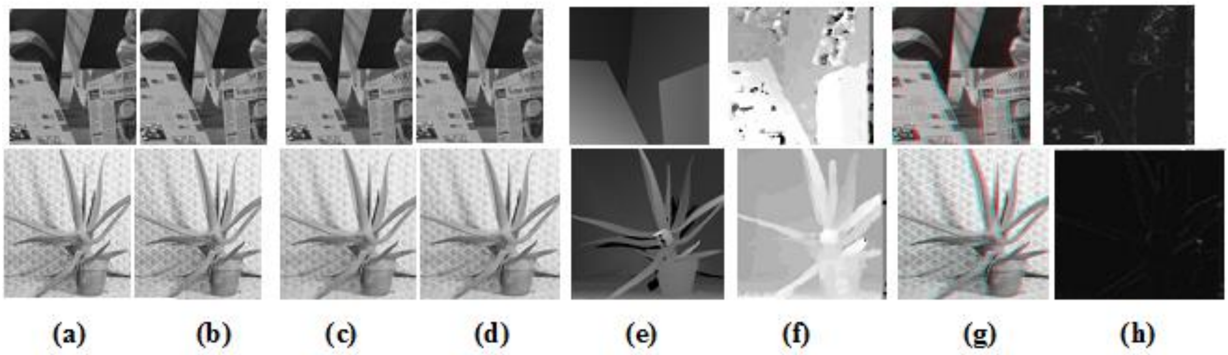


Fig (e) Stereo image Fig (f) Final Matching output

Fig 4 Stereo matching for 'TEDDY' image.

The performance evaluation of our proposed methodology is calculated by measuring the Average pixel bad match percentage. The bad match of our proposed method is reduced by 80% and it is proved to be more efficient than the existing algorithms. The average value obtained in our method has far exceeded when compared with these existing methods.



(a) & (b) Right and Left Stereo images (c) & (d) Right and Left images after bilateral filtering
(e) Ground Truth Image (f) Disparity image (g) Stereo image (h) Final Matching output
Fig 5: Evaluation results of stereo matching for 'VENUS' and 'ALOE VERA' data sets

Table 1: Various measures obtained from our proposed method

Input Images	Cost aggregation	RMS value	PSNR value
TEDDY	0.9794	2.3560	41.0285
VENUS	0.7771	0.9570	49.2004
ALOE VERA	0.286	5.8750	39.3233

Table 2: RMS and PSNR values for different matching methods

Matching method	RMS value	PSNR value
Proposed Methodology	**0.9570**	49.2004
Stereo matching using CLAHE[2013]	1.9145	39.6750
ESAW[2011]	3.2624	33.5420

Table 3: Percentage Bad match for proposed and existing works

Method	Venus			Teddy			APBP
	Nocc	All	Disc	Nocc	All	Disc	
Proposed Methodology	0.53	0.61	1.92	1.47	2.34	4.56	3.82
CLAHE matching approach (Rajeshkanna & Reeba Korah 2013)	0.4135	1.266	2.755	7.97	13.4	20.2	7.57
ESAW[22]	1.03	1.65	6.89	8.48	14.2	18.7	8.21
ADAPTIVE BP[20]	1.11	1.37	5.79	9.23	14.85	22.45	9.18

Table (3) shows the values obtained from our proposed method and the existing methods.

As per table (3), the various estimated disparity maps are evaluated by measuring the percentage of bad matching pixels for three subsets of an images like **Nocc** - the pixels in the non-occluded region, A**ll-** all the pixels, and D**isc** -the visible pixels near the occluded regions. The values for these subsets of the images are extracted for the proposed method and these values are then compared with those obtained using the different algorithms along with the average percentage bad pixel (APBP) and it is clear that our proposed method delivers better results than other existing works and this is shown in Figure 6

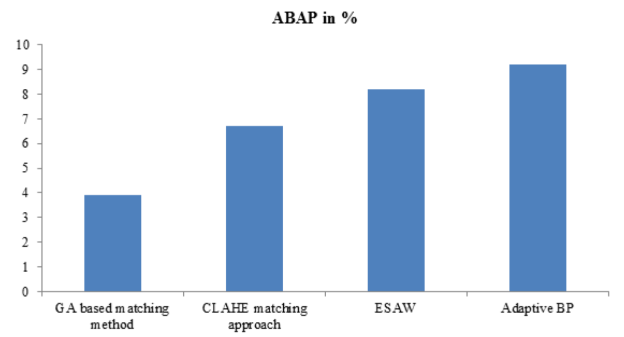


Fig. 6 Graphical representation of Average Percentage Bad matches for proposed and existing works

5. CONCLUSION

Stereo vision has become a very interesting sensing technology in the recent years. Due to the aptitude of certain non-parametric techniques, adaptive cost based stereo matching has been evolved . In this work, an efficient vision system with the aid of adaptive chromosome based cost aggregation approach is built. This approach employs various steps like cost matching, cost aggregation, disparity interpolation, disparity optimization which proved to be more realistic when compared with the other related works. The derived result shows that this genetic algorithm based method has increased the efficiency by 80% with reduced MSE value of 0.957 compared with other legacy algorithms and the flexibility of the system with respect to resolution. And the analysis also proved that it is very efficient with 80% of bad pixel error reduction compared with other legacy algorithms and attains 49 dB of PSNR. From the implementation point of view, this proposed approach shows minimum computational complexity and is faster in execution.

Upto now, little care had been given for the development of custom stereo vision algorithms for robotic applications and future research will continue attempts to achieve further improvements in the reduction of computational complexity and accuracy.

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