

# Dense Correspondence with Regional Support for Stereo Vision Systems

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**Abstract**—In this paper, a new method of stereo dense correspondence based on regional support is proposed. Using the information provided by high frequency components, a new regional point descriptor is introduced to improve matching accuracy. A detailed explanation on how to extend local correspondence algorithms to include the proposed regional support is provided. Results obtained by extending well known algorithms with the proposed approach demonstrate its effectiveness.

**Keywords**—Disparity map; Regional support; Stereo correspondence; Stereo matching; Stereo vision

## I. INTRODUCTION

Stereoscopic vision have been used on different applications, from robotics [1] to measurement systems [2]. Available in different configurations, but composed essentially by two cameras, these systems can provide three-dimensional information through the identification and evaluation of corresponding points in the captured images. These systems can be classified as active or passive [3]. Active systems emit some type of radiation and detect its reflection in order to evaluate an object or scene. Passive systems do not emit any radiation, but are based on the detection of natural radiation reflected by the environment. Most approaches use visible light.

In general three main problems need to be solved in order to obtain three-dimensional information: calibration, correspondence and reconstruction. Calibration step is related to the estimation of the parameters that describe the acquisition system. Correspondence step involves determining which element in an image captured from one point of view corresponds to a given element in an image captured from a different point of view. Reconstruction means recovering the depth information based on the parameters obtained in the calibration step and on a pair of corresponding points obtained in the correspondence step.

Correspondence is considered the main problem in stereoscopy. Occlusions, differences in lighting and projective distortions are just some of the factors that make point correspondence a complex task. For this reason, several methods have been proposed to address the problem. In general, cost functions based on similarity are defined to carry out the correspondence between the stereo pair images.

Based on the strategy used to perform the point correspondence, they can be classified as global, local or hybrid algorithms [4], [5]. Local algorithms present a significantly low precision of the calculated disparity maps when compared to global or hybrid algorithms. However, they are simple, present a reduced computational cost and have been successfully employed in many systems with real time requirements [6], [1].

In this work, improvements to local correspondence methods are proposed through the introduction of a regional support to the cost functions traditionally used. A general description of a stereo vision system is provided in section II. In section III, stereo correspondence is described, including its main approaches and problems. In section IV, the proposed regional support for local correspondence is introduced. The general steps of a local algorithm with regional support are presented in section V. In section VI local algorithms modified by the introduction of regional support are compared to its original versions and other local and global algorithms. Finally, in section VII the conclusions are presented.

## II. STEREO VISION SYSTEMS

Making use of a stereoscopic vision system is possible to recover the depth information of a given point in space from the relative distance between two points that represent it in images captured from different viewpoints. This distance is called disparity. As illustrated in Fig. 1, the disparity can be obtained by the difference of the coordinates of points  $m_l$  and  $m_r$ , which correspond to projections of a point  $M$  in space on the image planes of the cameras which compose the system.

In general, the depth information is obtained from a stereoscopic vision system through the treatment of three main problems: calibration, correspondence and reconstruction.

Calibration involves determining the parameters that describe the acquisition system. In Fig. II the basic geometry of a stereoscopic vision system consisting of two cameras is shown. The configuration assumed in this simplified model is rarely achieved in practice, since it is difficult to build a system where the binocular cameras have exactly the same characteristics and where they are perfectly aligned

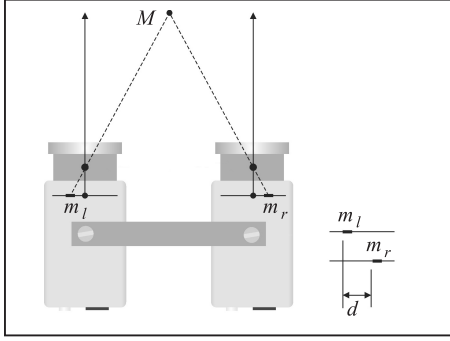


Figure 1. Simplified stereo configuration

as shown. For this reason, a more realistic model which consider the use of different cameras and where different orientations can be assumed is commonly used [3].

This model of stereoscopic vision system is described by different parameters, commonly grouped as intrinsic or extrinsic. The intrinsic parameters describe the geometrical and optical characteristics of the cameras. The extrinsic parameters describe the transformation that relates the coordinate systems of the two cameras to each other. Through these parameters is possible to perform the mapping between the coordinate systems of the image, the camera and the world.

Correspondence step involves determining which element in an image captured from one point of view corresponds to a given element in an image captured from a different point of view. It is the problem of main interest for this work, and it will be explained in details in section III.

Reconstruction means recovering the depth information based on the parameters obtained in the calibration step and on a pair of corresponding points obtained in the correspondence step. What can be reconstructed depends directly on what is known about the scene and the vision system [2]. In the case where where both intrinsic and extrinsic parameters are known we can perform a metrical reconstruction. If only the intrinsic parameters are known, we can perform a reconstruction up to a scale factor. In the case where no intrinsic or extrinsic parameters are known and where only the information of corresponding points is known we can only accomplish the reconstruction subject to an overall unknown projective transformation.

### III. DENSE CORRESPONDENCE

As described in section II, we can retrieve depth information of a point in space from the disparity. To determine the disparity it is necessary to match elements in the captured images, identifying points on the left image and on the right image that are projections of the same point in the three-dimensional observed scene. This procedure, called correspondence, is one of the most researched topics in

computer vision.

To perform the points matching, two main issues must be considered: what elements will be matched and which similarity criteria will be used. Based on what points are matched, we can classify many existing matching algorithms into two main classes: the dense correspondence methods and sparse correspondence methods. The dense correspondence methods aim to match all points of the images. The sparse correspondence methods match a reduced set of relevant image points.

The dense correspondence methods are particularly interesting since they provide a lot of information about the observed scene. For the algorithms that implement this approach, the input is a pair of images provided by the binocular system, usually rectified [3]. Rectification of a stereo image pair is related to apply geometrical transformations in the images in order to align the epipolar lines. These transformations are based on calibration parameters. The rectification is important since it reduces the matching process from a 2D search problem to a 1D search problem.

Taking one of the rectified images as reference, for each point in this image a search for the corresponding point in the other image is performed, according to some similarity criteria. The disparity is calculated for each pair of matched points as the value of the relative distance between its coordinates. The value of the disparity is stored as the value of intensity in the current position in a third image, called disparity map. The intensity values for each point in the disparity map store depth information of the scene, since the disparity is inversely proportional to depth [1].

In general, the dense correspondence algorithms are classified as local or global, based on the strategy used to match the points [4]. Additionally, some algorithms can be classified as hybrids, since they make use of local and global approaches combined with specific approaches. Many of these hybrid algorithms calculate the disparity for entire regions by adjustment of plans, based on reliable correspondences obtained by local methods [6].

#### A. Local correspondence approach

In local correspondence algorithms it is assumed that the image points are involved by a window of neighboring elements where the disparity is the same. This way, the correspondence for each point is performed based on the correspondence of these windows.

The basic method used for correspondence in this approach is the correlation [3]. Given a stereo image pair, one of the images is chosen as reference and the size of a square window to be used in the matching process is defined. For each point in the reference image, the following steps are done:

- 1) Centralize the window in the point of interest in the reference image;

- 2) Do the correlation between the window located in the reference image with a second window, moving it on all positions through the search space in the second image;
- 3) Select the point in the second image that corresponds to the element of interest in the first image, choosing the position where the correlation minimizes the employed cost function;
- 4) The disparity is given by the relative difference between the central position of the windows. Store the disparity values in one third image, at the same coordinates of the central point of the window in the reference image.

The result is a dense map of disparities, composed by the calculated disparity for each element in the reference image.

The correspondence algorithms require that the input images are rectified. Moreover, search space is also limited by the possible maximum and minimum disparities for a given stereo configuration [7].

The correspondence methods by correlation use cost functions that consider the similarity of the intensity values of each image point, such as the sum of the squared differences (*SSD*) and the sum of absolute differences (*SAD*). A cost function using similarity of the intensity values *SAD* is given by

$$C_{sad}(x, y, d) = \sum_{i,j=-n}^n |D_{Il}(x + j, y + i) - D_{Ir}(x + d + j, y + i)| \quad (1)$$

where  $d$  is a given disparity,  $D_{Il}(x, y)$  and  $D_{Ir}(x, y)$  correspond to a description function based on intensity referring to the left and right images. A square window of size  $2n + 1$  is used.

In the described correspondence algorithm, the intensity assumes the role of a descriptor for each image point. This description doesn't show robustness, since the intensity value of each point is sensible to influences such as differences in the gain of sensors, radiometric variations, among others.

In an effort to solve this problem, *LOG* filter [1] is widely used to normalize the images. *LOG* filter is composed by a Gaussian filter and a Laplacian filter. The Laplacian filter reduces illumination influences, since its result is zero in areas with constant intensity and it is negative or positive next to edges with high intensity gradient. However, Laplacian filter is highly sensible to noise influence. For this reason, the Gaussian filter is applied before it to minimize this problem.

Fig. 2 illustrates the Tsukuba stereo image pair normalized using the *LOG* filter. The original right image presents a significant difference in the luminous intensity when compared to the original left image (a and b). However, applying *LOG*

filter in both images we achieve a very similar result (c and d).

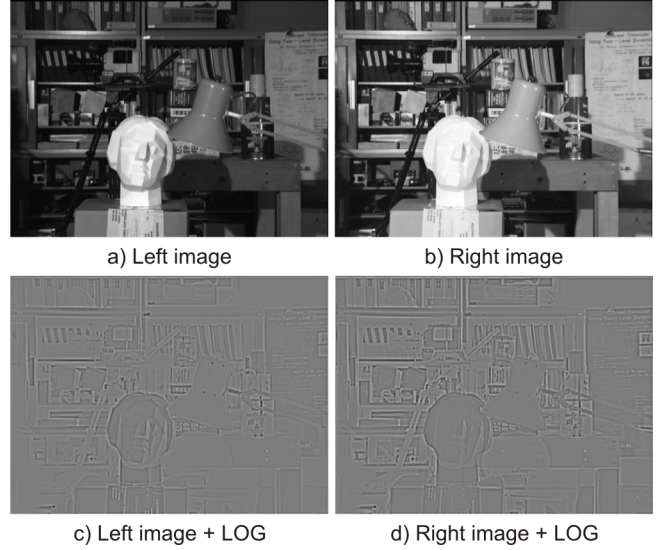


Figure 2. LOG normalization - a,b)Original c,d)Filtered

The use of *LOG* normalization of the images increases the quality in the generated disparity maps. However, large homogeneous regions, resultant of areas where the intensity derivative is low are obtained. In these cases, classical similarity criteria still don't present satisfactory results.

Fig. 3 illustrates the existing problem in the description of points based in intensity during the correspondence process. For a point on the right image, a matching search is performed over the points in a specific search space in the left image. In the illustrated correspondence process, only the descriptor based on intensity  $D_i(x, y)$  is used. It is possible to observe how the values that describe each point can be similar. The use of a cost function based only on this descriptor can yield in the occurrence of arbitrary correspondences.

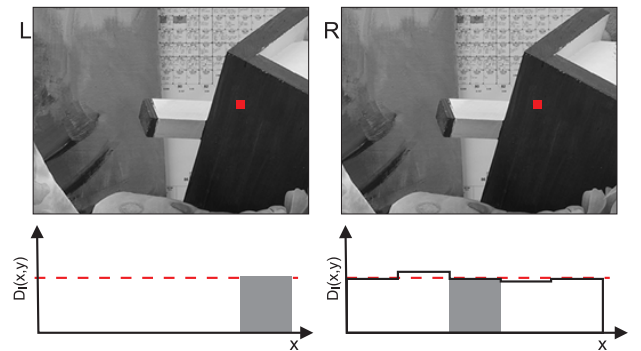


Figure 3. Description using intensity

The use of wide windows can be an option, since it reduces the number of windows completely overlapped in a homogeneous region. However, when this resource is used, the precision of disparity in the edges become very poor.

### B. Global correspondence approach

The methods that follow the global approach propagate the disparity information from one point to its neighbors. To do this, employ the minimization of some function of energy over a large region of the image. The dynamic programming algorithm is one of these algorithms [8]. It uses a cost function that considers the number of occlusions, correspondences and a measure of dissimilarity. An exhaustive search for the best of disparity among the possible solutions according to the cost function is performed to each row of the image.

To each possible matching sequence  $M$ , a cost is given by:

$$\gamma(M) = N_{occ}k_{occ} - N_m k_r + \sum_{i=1}^{N_m} d(m_{ei}, m_{di}) \quad (2)$$

The cost  $\gamma(M)$  measure the probability that a sequence has to be a right correspondence. The parameters  $N_{occ}$  and  $N_m$  represent the number of occlusions and of alignments.  $k_{occ}$  and  $N_r$  are the respective constants of penalty and reward, and  $d(m_{ei}, m_{di})$  is a dissimilarity function based on intensity of left and right image points. The optimum alignment sequence is achieved employing an exhaustive search using a dynamic programming algorithm.

The mains advantage of these kind of algorithm is the treatment of homogeneous regions. However, they usually employ parameters that are difficult do define.

## IV. PROPOSED METHOD: LOCAL CORRESPONDENCE WITH REGIONAL SUPPORT

In the correspondence process described in section III-A, the intensity assumes the role of a descriptor for each image point. It is observed, however, that a description based on intensity is not enough to identify a pair of corresponding points uniquely. The same occurs with the human visual system when we observe a surface extremely smooth or in poorly illuminated environment. In these conditions, in the lack of fine details that let us guide correspondence between points observed by eyes, in a natural way we appeal to the information supplied by high frequency elements located in the peripheral region to determine the depth.

The proposed method in this work attempt to model this behavior. The main idea is to describe each image point with an intensity descriptor and a regional descriptor. The regional descriptor must aggregate peripheral information provided by components of high frequency surrounding the observed point. This way, we can define a cost function with regional support as

$$C_r(x, y, d) = S_i(x, y, d) + \alpha S_r(x, y, d) \quad (3)$$

where  $S_i(x, y, d)$  is a similarity function based on an intensity descriptor  $D_I(x, y)$ ,  $S_r(x, y, d)$  correspond to a similarity function based on a regional descriptor  $D_R(x, y)$  and  $\alpha$  correspond to the weight employed to the function of regional support.

Fig. 4 illustrates the effect of the description of points with regional support during the correspondence process. For a point on the right image, a matching search is performed over the points in a specific search space in the left image. Different from the situation illustrated in Fig. 3, in this case both the intensity descriptor  $D_I(x, y)$  and the regional descriptor  $D_R(x, y)$  are used. It is possible to observe how a description based on this combination of descriptors allows a better distinction between points. A cost function based on these descriptors permits a better selection of the correct correspondences.

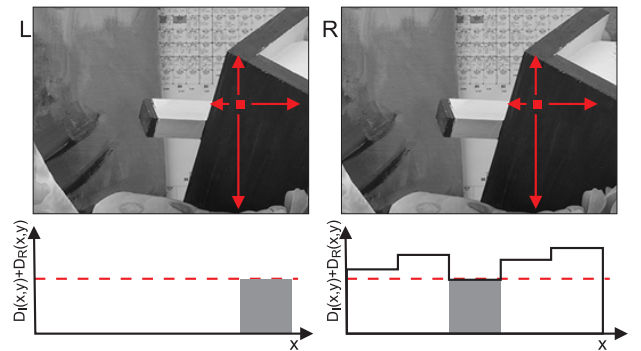


Figure 4. Description using intensity and regional support

A similarity function  $S_r(x, y, d)$  based on regional descriptors  $D_R(x, y)$  is given by

$$S_r(x, y, d) = \sum_{i,j=-n}^n \sqrt{D_v(x, y, d)^2 + D_h(x, y, d)^2}. \quad (4)$$

The terms  $D_v(x, y, d)$  and  $D_h(x, y, d)$  in 4 are given respectively by

$$D_v(x, y, d) = \frac{D_t(x, y)}{D_t(x, y) + D_b(x, y)} - \frac{D_t(x + d, y)}{D_t(x + d, y) + D_b(x + d, y)} \quad (5)$$

and

$$D_h(x, y, d) = \frac{D_l(x, y)}{D_l(x, y) + D_r(x, y)} - \frac{D_l(x + d, y)}{D_l(x + d, y) + D_r(x + d, y)}, \quad (6)$$

where  $D_t(x, y)$ ,  $D_b(x, y)$ ,  $D_l(x, y)$  and  $D_r(x, y)$  are regional descriptors that represent the distance between the observed point and the next component of high frequency above, below, to the left and to the right, respectively. Here, both  $D_v(x, y, d)$  and  $D_h(x, y, d)$  are adimensional in order to handle possible dimensional differences introduced by perspective in the captured images.

## V. ALGORITHM SUMMARY AND OPTIMIZATIONS

This section presents the general steps of a local correspondence algorithm with regional support.

### A. Calculation of Regional Descriptors

Due to the insertion of the regional support term in the correspondence cost function, we need to calculate the regional descriptors for each image. These descriptors are based on the distance between each point and the components of high frequency that delimit the homogeneous region where the point is located. To identify these components we can make use of edge filters. However, the result gotten with these filters is normally noisy.

An important consideration is the non obligation to apply the regional support to the whole image. When the intersection between the correlation window and components of high frequency is different from zero, we don't need it because the performance of similarity functions based on intensity is satisfactory. Hence, we can use a segmentation method based on the variance of the intensities to isolate the desired homogeneous regions.

A segmentation based on the intensities variance map shows reduced computational cost when compared to other techniques, e.g. Mean Shift [8]. The variance map can be calculated by

$$\sigma_L^2(x, y) = \frac{1}{N^2} \sum_{i,j=-n}^n L(x + j, y + j)^2 - \mu_L(x, y)^2, \quad (7)$$

where  $N = (2n + 1)^2$  and  $\mu_L(x, y)$  is the average of the intensity values [9].

We can isolate the homogeneous regions of the image applying a global limiarization over the calculated map of variances. From the resultant binary image, we can calculate the distance maps corresponding to the regional descriptors  $D_t(x, y)$ ,  $D_b(x, y)$ ,  $D_l(x, y)$  and  $D_r(x, y)$ .

Fig. 5 illustrates the process described above. Fig. 5-a presents the original image, in this case the left image of the Teddy stereo pair. Fig. 5-b presents the variance map calculated using the original image. Fig. 5-c presents the

result of the binarization of the variance map. Furthermore, Fig. 5-d presents the distance map corresponding to the descriptor  $D_t(x, y)$ , calculated over the binary image.

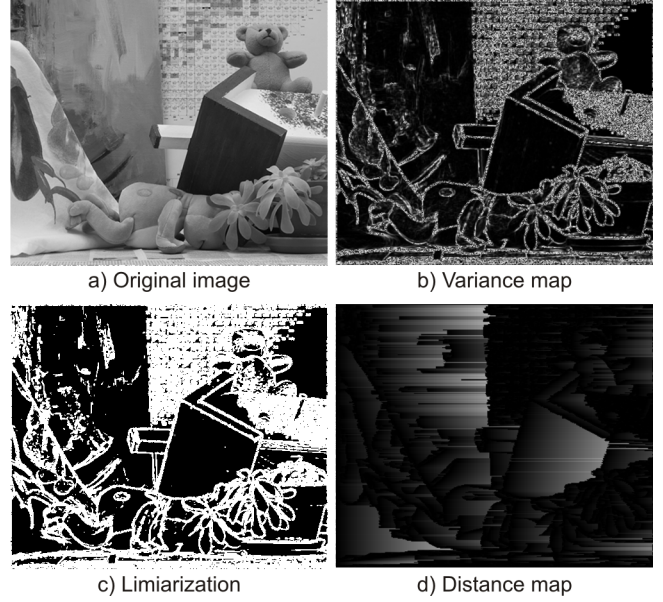


Figure 5. Calculation of regional description

With the distance regional descriptors, we can calculate the adimensional descriptors maps  $D_v(x, y, d)$  and  $D_h(x, y, d)$  according to 5 and 6.

### B. Correspondence

From 3 we can define many cost functions from the combination between different similarity functions based on intensity and region. Since the regional similarity function presented in 6 is essentially a correlation function, it fits very well to intensity similarity function of the same nature.

Therefore, using the intensity similarity function presented in 1 and the regional similarity function presented in 4, we can define a new cost function based on *SAD* and with regional support rewriting the cost function with regional support given by 3 as

$$C_{sadr}(x, y, d) = \sum_{i,j=-n}^n |D_{Il}(x + j, y + i) - D_{Ir}(x + d + j, y + i)| + \alpha \sqrt{D_v(x, y, d)^2 + D_h(x, y, d)^2}. \quad (8)$$

Here, the calculation of the term of regional support is performed using the maps of descriptors previously calculated, as described in section V-A.

Finally, once we have computed the cost values over all disparity space search, the corrected correspondence is

selected according to Winner-Takes-All approach (WTA) [4].

### C. Error elimination

In order to eliminate false correspondences, the left-right consistency verification method is employed [10]. This consistency is carried out for each point to verify if the correspondences calculated are coherent when the reference image that guides the correspondence is modified.

The process of verification can be described as follows. First, for each point in the left image the best correspondence with the points in the right image is calculated. Then, the reference image is inverted and, for each point in the right image, the best correspondence with the points in the left image is calculated. Finally, only are considered the points where the correspondence from left to right and the correspondence from right to left are coherent. In case that the values of disparity diverge, the points are marked attributing value zero.

In a following step, the points with value of disparity equal to zero are removed through interpolation.

### D. Optimizations

In a correspondence algorithm based on correlation of windows, the most expensive task is the calculation of the correspondence cost values. A cost function based on similarity *SAD* can be calculated efficiently exploring the fact that neighboring windows overlap [11] each other. The same characteristic can be observed in the cost function presented in 8.

In neighboring windows with the same disparity, overlapping points will have the same values of absolute difference both for the intensity descriptor as for regional descriptor. Therefore, a new value of cost can be calculated for the current window using the value calculated for an old window deducting the values from the points that are part only of the old window, and adding the values of the points that are part of the new window. This optimization still presents the advantage to make the computational cost practically independent of the window size used in correlation.

Additionally, algorithms based on correlation can be optimized through the use of resources of parallel processing SIMD available on diverse architectures [11], [6]. Since the inclusion of regional support does not modify the correlation based behavior of the algorithms where it is applied, it can also take benefits of these advantages.

## VI. EXPERIMENTAL RESULTS

The comparison of the results obtained from different dense correspondence methods is presented. To do so, well known algorithms representing both local and global approaches were selected and implemented. Also, two versions of algorithms based on the proposed approach were created. All algorithms were included in the

S2i3DLib library and are available as open source code at <http://s2i.das.ufsc.br/s2i3dlib>.

To represent the local approach, algorithms based on single window correlation [9] and multiple window correlation [10] were implemented. To represent the global approach, the Dynamic Programming algorithm [12] was selected. In order to reduce the number of wrong correspondences, the left-right consistency check was applied to all algorithms.

The cost function with regional support presented in 3 allows a diversity of combinations, due to the use of the different intensity similarity functions and regional similarity functions. So, both simple and multiple window correlation algorithms were extended in order to create new algorithms based on the local/regional approach described in section IV and the steps described in section V.

A list of all algorithms used in the comparison is presented in the Table I.

Table I  
COMPARED ALGORITHMS

Abbreviation	Description	Approach
WTA SAD SW	Single window (SAD/WTA)	Local
WTA SADR SW	Single window with regional support (SADR/WTA)	Local / Regional
WTA SAD MW	Multiple windows (SAD/WTA)	Local
WTA SADR MW	Multiple windows with regional support (SADR/WTA)	Local / Regional
DP	Dynamic programming	Global

The experiments were carried out using a set of stereo images with ground truth [4]. We used the reference stereo image pairs Tsukuba, Teddy, Cones and Venus. The reference stereo image pairs present different characteristics such as presence of complex objects, objects in different depths generating varied occlusions, regions without texture or with homogeneous intensity, among others. Hence, they are ideal for evaluation of correspondence algorithms under different criteria.

Disparity maps for each stereo image pair were calculated using each one of the implemented algorithms. In the Fig. 6 the ground truth and the disparity maps calculated for the Tsukuba stereo pair are presented.

In general, the window correlation algorithms present good results on regions rich in texture and details. However, the correspondences are not reliable in homogeneous regions or in regions with repetitive patterns. The DP global algorithm presents good average results. However, stripe patterns are introduced in the estimated disparity maps.

The introduction of regional support improve the obtained results for local algorithms, especially in images with homogeneous regions. This characteristic is clearly visible in the comparison of results for the Teddy stereo pair presented on Fig. 7. The original version of the local algorithm fail when estimating the correspondences for the homogeneous region corresponding to the roof of the little house present in the

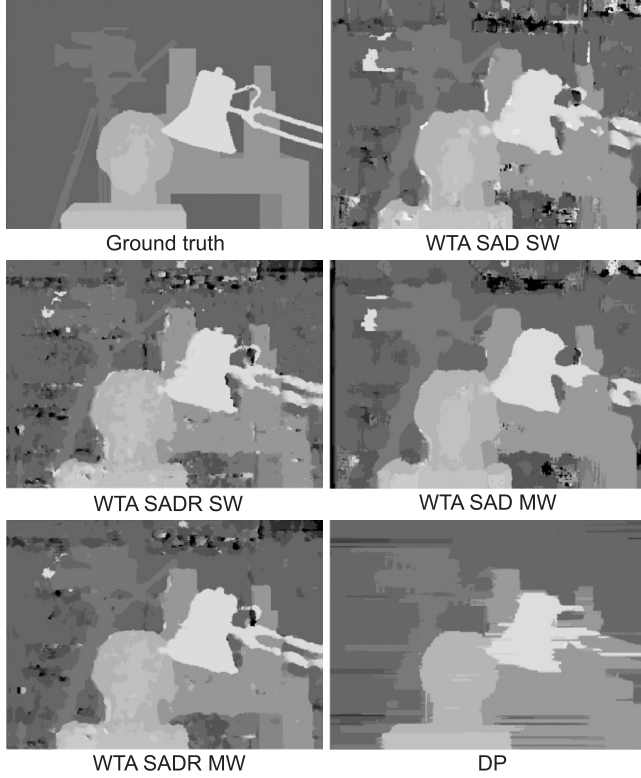


Figure 6. Calculated disparity (tsukuba)

image. It's version including the proposed regional support is able to do that.

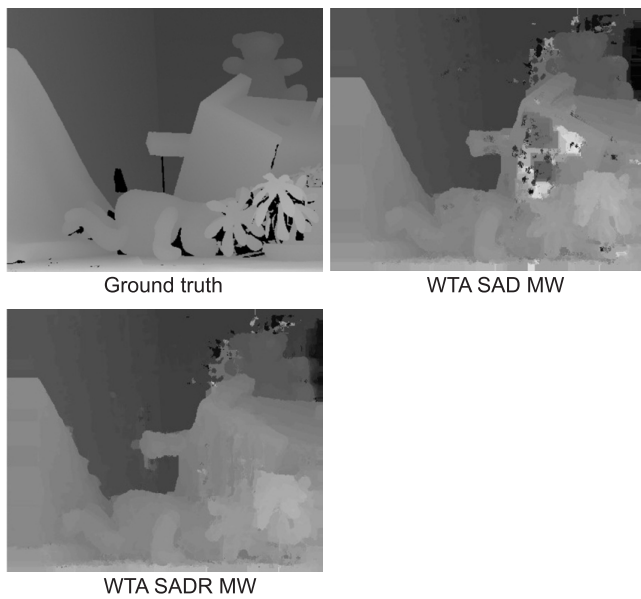


Figure 7. Calculated disparity (Teddy)

For a more objective evaluation, a comparison of the

evaluated algorithms was performed using the percentage of incorrect correspondences as a quality measure. The percentage of incorrect correspondences is given by

$$E = \frac{1}{N} \sum_{x,y} |d_c(x,y) - d_t(x,y) > \delta_d| \quad (9)$$

where  $d_c(x,y)$  is the calculated disparity,  $d_t(x,y)$  is the true disparity and  $\delta_d$  is the value of tolerance to the disparity error [4].

Table II shows the general error presented in the calculation of the disparities with the different evaluated methods. The employed search space was the same suggested by the reference base, and all methods run with constant parameters on all 4 stereo pairs. For the calculation of the general error a value to  $\delta_d$  equal to 1 was used.

Table II  
GENERAL ERROR OF DISPARITIES (%)

Method	Tsukuba	Venus	Teddy	Cones	$\bar{x}$
WTA SAD SW	14.60	17.60	30.90	27.50	22.65
WTA SADR SW	8.45	9.45	26.90	17.60	15.60
WTA SAD MW	9.51	10.70	26.70	22.80	17.43
WTA SADR MW	<b>5.96</b>	<b>7.12</b>	22.80	<b>15.00</b>	<b>12.72</b>
DP	7.98	10.70	<b>20.20</b>	20.90	14.95

The regional support method proposed in this work raised the results precision for local correspondence algorithms where it was applied. Additionally, the multiple windows algorithm with regional support presented superior results in relation to the obtained using algorithms with global approaches.

Table III shows the running time presented in the calculation of the disparities with the different evaluated algorithms.

Table III  
RUNNING TIMES (S)

Method	Tsukuba	Venus	Teddy	Cones
WTA SAD SW	0.11	0.19	0.56	0.68
WTA SADR SW	0.52	1.05	2.23	2.25
WTA SAD MW	0.39	0.97	2.44	2.45
WTA SADR MW	1.66	3.35	9.32	9.32
DP	0.09	0.16	0.25	0.35

The DP global algorithm has presented the best average time, followed by the single window local algorithm. We consider that only these algorithms are suitable to real time applications.

The extension of local algorithms to include regional support has presented a considerable increase in computational cost. This may not be a problem to applications where real time requirements are not present. However, if real-time is desired, an extra effort on optimization is necessary [9].

## VII. CONCLUSIONS

In this work a new method of stereo correspondence with regional support is proposed. This method, based on the

addition of a similarity function using regional descriptors to commonly used cost functions, improves the performance of already known local correspondence algorithms. Moreover, it obtains better results than methods employing global correspondence.

Being simple and presenting superior results, it can be employed to calculate the initial disparity estimative in more elaborated correspondence methods [13], substituting those currently used.

The presented results have also been evaluated using the widely used on-line evaluation framework Middlebury Stereo Vision [4], confirming the validity of the proposed method.

Future work includes reducing the computational cost for algorithms employing this method through the use of General Purpose Computation on Graphics Processing Unit (GPGPU).

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