Fast Edge-Based Stereo Matching and Geometric Parameters

P. Moallem and K. Faez

Electrical Engineering Department, Amirkabir University of Technology, Hafez Avenue, Tehran, Iran
e-mail: m7523903@aut.ac.ir, kfaez@aut.ac.ir

Abstract—The reduction of the search region in stereo correspondence can improve the performance of the matching process in terms of execution time and accuracy. For the edge-based stereo matching, we establish the relationship between a search space and parameters such as relative displacement of the edges, the disparity under consideration, the image resolution, the CCD dimension, and the focal length of the stereo system. Then, we propose a novel matching strategy for the edge-based stereo. Afterward, we develop a fast algorithm for the edge-based stereo with a combination of the obtained matching strategy and the multiresolution technique by using the Haar wavelet. Considering the conventional multiresolution techniques using the Haar wavelet, the execution time of our method (including feature extraction and feature matching) are decreased by 37%. Moreover, the failed rate and the error are also decreased. Theoretical investigation and experimental results show that our algorithm has a very good performance; therefore, this new algorithm is very suitable for fast edge-based stereo applications like stereo robot vision.

1. INTRODUCTION

Stereo vision refers to the ability to infer information on 3D structures and the distances of a scene from at least two images (left and right) taken from different viewpoints. A stereo system must solve two essential problems: correspondence and reconstruction [1]. The correspondence consists of determining which item in the left image corresponds to which item in the right image. It is usually not a good practice to try to find the corresponding points for all pixels. For example, a point in a uniform region in one image may correspond to many points in the corresponding region in the other image. Thus, feature points or matching primitives are selected so that an unambiguous match can be found [1]. The depth in a stereo system is related to the inverse of the disparity, which is the difference between the position of the corresponding points in the left and right images. The disparity of the image points forms the so-called disparity map, which can be displayed as an image. If the geometry of the stereo system is known, the disparity map can be converted to a depth map of the viewed scene. This process is called the reconstruction step in stereo algorithms.

Edge-based stereo matching is a popular method in some fast stereo vision applications [2, 3]. Finding the corresponding edges is considered the most difficult part of the edge-based stereo matching algorithms. Usually, the correspondence for a feature point in the first image is obtained by searching in a predefined region of the second image, based on the epipolar line [1] and the maximum disparity constraint [4]. The reduction of the search region can increase the performance of the matching process in terms of execution time and accuracy. Traditionally, the hierarchical multiresolution techniques using wavelet transform as fast methods are used to decrease the search space and, therefore, increase the processing speed [5].

Considering the limit of the directional derivative of the disparity [6] (which sometimes is incorrectly called a disparity gradient limit), we could restrict the search space in the edge-based stereo correspondence [7, 8]. In this paper, we establish a relationship between the search space and the parameters, under consideration, such as focal length and disparity. In the next section, we briefly discuss the concept of DDD (the directional derivative of disparity). Then, we establish a relationship between the DDD and the displacement of feature points (such as edges) in the left and right images. Considering the pdf of DDD, we have already obtained a probabilistic relationship between the search space and the geometric constraint [9]. We extend it and suggest a fast matching strategy for the edge-based stereo correspondence on the base of obtained relationships. Considering the hierarchical multiresolution technique using the Haar wavelet [5] and our matching strategy [7–9], we develop a fast edge-based stereo matching algorithm. Finally, we discuss the implementation results.

2. DIRECTIONAL DERIVATIVE OF DISPARITY

Figure 1 shows the geometry of cameras for a basic stereo system where the camera optical axes are parallel to each other and perpendicular to the baseline connecting the cameras L and R. O_L and O_R are the optical centers of the left and right camera, respectively, and O_L and O_R are the origins of the left and right image plane, respectively. For a point \( P(X, Y, Z) \) in a 3D scene, its projections onto the left image and the right image are...
Suppose a virtual camera is placed in the middle of the average distance between \((x_l, y_l)\) and \((x_r, y_r)\) \([10]\). Considering this camera geometry, it can be shown that \(y_l = y_r\), and the disparity \(d\) is inversely proportional to the depth \(Z\). We have \(d = \frac{bf}{Z}\), where \(f\) is the focal length of the camera lens and \(b\) is the separation of two cameras or the baseline \([1]\). Given the two points \(P1\) and \(P2\) in the 3D scene, the DDD can be defined as the difference in disparities divided by the cyclopean separation, where cyclopean separation is the average distance between \((p^1_l, p^1_r)\) and \((p^2_l, p^2_r)\) \([10]\). Suppose a virtual camera is placed in the middle of the cameras \(L\) and \(R\), i.e., at the position of origin \(O_c\). Therefore, we have

\[
\begin{align*}
  d_2 &= x^2_l - x^2_r, \\
  d_1 &= x^1_l - x^1_r, \\
  p_c &= \frac{p^1_l + p^1_r}{2}, \quad p^1_c = \frac{p^1_l + p^1_r}{2}.
\end{align*}
\]

With these definitions, \(d_a\) can be defined as \([10]\)

\[
d_a = \frac{(d_2 - d_1)}{r} = \frac{(d_2 - d_1)}{\|p^c - p^1_c\|},
\]

where \(\|\cdot\|\) denotes the vector norm. The value of \(d_a\) can be used to define various stereo-matching constraints. A brief summary follows \([8]\):

- \(d_a > 2\) — violation of nonreversal order constraint;
- \(d_a = 2\) — violation of uniqueness constraint;
- \(d_a < 1.1\) (or 1.2) — empirical limit of the DDD;
- \(d_a \leq 1\) — figural continuity constraint.

If we substitute the relation (1) into Eq. (2), we have

\[
\begin{align*}
  d_a &= \frac{(d_2 - d_1)}{\|p^c - p^1_c\|} \\
  &= \frac{2(x^2_l - x^2_r) - (x^1_l - x^1_r)}{\sqrt{\left(p^1_l + p^1_r\right)^2 + (p^1_l - p^1_r)^2}} \\
  &= 2 \frac{(x^l - x^r) - (x^1_l - x^1_r)}{\sqrt{(p^1_l + p^1_r)^2 + (p^1_l - p^1_r)^2}}.
\end{align*}
\]

3. DDD AND THE DISPLACEMENTS OF EDGES

Suppose the feature points in the left image are nonhorizontal edges in successive scan lines. We want to find their correspondences in the right image. Considering the points \(P1\) and \(P2\) in Fig. 1, we define the displacement of \(P1\) and \(P2\) in the left and the right images, \(\Delta x_l, \Delta x_r, \Delta y_l, \Delta y_r\), as

\[
\begin{align*}
  \Delta x_l &= x^2_l - x^1_l, \\
  \Delta x_r &= x^2_r - x^1_r, \\
  \Delta y_l &= \Delta y_r = \Delta y = y^2 - y^1.
\end{align*}
\]

Suppose we want to match the continuous nonhorizontal edges in successive scan lines; in this case, we have \(\Delta y = \Delta y_r = 1\). Therefore, the DDD between \(P1\) and \(P2\) can be defined as \([7, 8]\)

\[
d_a = \frac{2(\Delta x_l - \Delta x_r)}{\sqrt{\left(\Delta x_l + \Delta x_r\right)^2 + (\Delta y_l + \Delta y_r)^2}}.
\]

For the edge points in the successive scan lines, we have \(\Delta y = 1\); so, Eq. (5) can be simplified as

\[
d_a = \frac{\Delta x_l - \Delta x_r}{\sqrt{\frac{\left(\Delta x_l + \Delta x_r\right)^2}{2} + 1}}.
\]

Suppose \(x^l_1 = x^l_2\); this means that \(\Delta x_l = 0\). Considering Eq. (6), we can find the upper and the lower limits of \(d_a\) in some ranges of \(\Delta x_r\). Some results are shown in Table 1. As the \(\Delta x_r\) range is increased, the \(|d_a|\) limit approaches 2, which violates the uniqueness constraint in the stereo system \([8]\). For other values of \(\Delta x_l\) and \(\Delta x_r\), the ranges of \(d_a\) can be computed. Some results for \(\Delta x_l = +1\) are shown in Table 2. The other cases \((\Delta x_l = -1, \Delta x_l = +2, \Delta x_l = -2)\) can be simply computed.
In Table 2, \( \Delta d_{a} \) is +2 in the case of \( \Delta x_{r} = +1 \) and \( \Delta x_{r} = -1 \). Since the limit of \( |d_{a}| \) is 2, there is no need to decrease \( \Delta x_{r} \) lower than -1. On the other hand, since \( \Delta x_{r} \) can be increased toward positive infinity, then \( d_{a} \) also approaches -2, which is the lower limit of \( d_{a} \) [7, 8].

### Table 2. The range of \( d_{a} \) for some values of \( \Delta x_{r} \) in the case of \( \Delta x_{r} = +1 \)

<table>
<thead>
<tr>
<th>Some values of ( \Delta x_{r} )</th>
<th>Range of ( d_{a} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0, 1, 2</td>
<td>-0.55 &lt; ( d_{a} &lt; +0.89 )</td>
</tr>
<tr>
<td>-1, 0, 1, 2, 3</td>
<td>-0.89 &lt; ( d_{a} &lt; +2.0 )</td>
</tr>
<tr>
<td>-1, 0, 1, 2, 3, 4</td>
<td>-1.11 &lt; ( d_{a} &lt; +2.0 )</td>
</tr>
<tr>
<td>-1, 0, 1, 2, 3, 4, 5</td>
<td>-1.26 &lt; ( d_{a} &lt; +2.0 )</td>
</tr>
</tbody>
</table>

### Table 3. Some of the CIL geometric parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizontal cells in CCD array</td>
<td>576</td>
</tr>
<tr>
<td>Horizontal pixels in computer frame buffer</td>
<td>576</td>
</tr>
<tr>
<td>Distance between sensor elements, mm</td>
<td>2.3e-2</td>
</tr>
<tr>
<td>Focal length, mm</td>
<td>57</td>
</tr>
</tbody>
</table>

In Table 2, \( \Delta d_{a} \) is +2 in the case of \( \Delta x_{r} = +1 \) and \( \Delta x_{r} = -1 \). Since the limit of \( |d_{a}| \) is 2, there is no need to decrease \( \Delta x_{r} \) lower than -1. On the other hand, since \( \Delta x_{r} \) can be increased toward positive infinity, then \( d_{a} \) also approaches -2, which is the lower limit of \( d_{a} \) [7, 8].

### 4. DDD RANGES AND DISPARITY VALUES

In the previous section, the DDD range was related to the \( \Delta x_{r} \) value and the \( \Delta x_{r} \) range. When \( \Delta x_{r} \) is known, the \( \Delta x_{r} \) range can be selected if the range of \( d_{a} \) is already determined. In this section, we will show that the range of \( d_{a} \) is a probabilistic phenomenon and depends on the stereo system parameters and the disparity value [9]. The pdf of DDD for a point \((x_{i}, y)\) in the left image with disparity \( d \) may be found by mapping the DDD of Eq. (2) into a tangent direction at \([X, Y, Z]\) in the 3D space of the scene and using the relationship to transform the pdf of the scene coordinate tangent to the pdf of the DDD. Performing these calculations and approximating the results for simplification yields [11]

\[
P_{d_{a}}(d_{a}) = \frac{f/d}{2(1 + (f/d)^{2}d_{a}^{2})^{3/2}}.
\] (7)

The approximation performed on Eq. (7) for simplification is only valid for proper ranges of the camera parameters and geometry of the stereo system. Typically, \( f \) is in the range of 10 to 60 mm and \( b \) may be 5 to 20 cm [6].

The general shape of this pdf is similar to a Gaussian function. Moreover, this pdf explicitly depends on the disparity under consideration \((d)\) and the focal length of the cameras \((f)\), or, equivalently, on the depth and the intercamera baseline (since \(fbd = Zb\)).

As an example, consider the CIL image database (Calibrated Imaging Laboratory at CMU, Carnegie Mellon University) [12]. Some geometric parameters of the CIL images are listed in Table 3. Considering this table, the focal length of the CIL is about 2478 pixels \((57 \text{ mm/23 } \mu \text{m} = 2478)\). Figure 2 shows the pdfs for various disparity values as a function of the DDD values. These functions have some sharp peaks near zero DDD and become wider when the disparity increases.

Assume that the range of \( d_{a} \) is \( Rd_{a} = \{ d_{a}^{l} < d_{a} < d_{a}^{H} \} \); therefore, \( P(d_{a} \in Rd_{a}) \) can be obtained by integrating Eq. (7) over \( Rd_{a} \) as

\[
P(d_{a} \in Rd_{a}) = \int_{d_{a}^{l}}^{d_{a}^{H}} P_{d_{a}}(d_{a})d(d_{a}).
\] (8)

When \( Rd_{a} \) is a subset of \([-2, +2]\), we have a restricted search region and so we must allow for some error. Assume that this error is less than 0.5%, so that \( P(d_{a} \in Rd_{a}) > 0.995 \). In a typical stereo algorithm, sometimes up to 10% error in the matching stage can be acceptable; therefore, the condition \( P(d_{a} \in Rd_{a}) > 0.995 \) is suitable [9], since the error due to the search region selection is less than 0.5%. We are interested in finding the maximum of the disparity \((d_{a}^{\max})\) so that \( P(d_{a} \in Rd_{a}) > 0.995 \). For example, suppose \( \Delta x_{r} = +2 \), \( \Delta y = +1 \), and \( \Delta x_{r} = \{0, +1, +2, +3\} \) so that \( d_{a} \) is varied between \( d_{a}^{l} = -0.37 \) and \( d_{a}^{H} = +2.0 \). We want to find the disparity \( d_{a}^{\max} \) so that \( P(d_{a} \in Rd_{a}) > 0.995 \). We increase \( d \) from zero and compute \( P(d_{a} \in Rd_{a}) \) for each
value of \( d \) considering Eq. (8). The maximum value of \( d \) that satisfies the condition \( P(d_a \in R_d) > 0.995 \) is denoted by \( d_{\text{max}} \). In this example, \( d_{\text{max}} \) is 130 pixels.

Tables 4 and 5 show the relations between \( \Delta x_l, \Delta x_r \), and \( d_{\text{max}} \) for \( P(d_a \in R_d) > 0.995 \); for other values of \( \Delta x_i \), the computations are similar.

### 5. FAST ALGORITHM

Our matching algorithm has two stages: edge extraction and edge matching. The edge extraction stage consists of identifying nonhorizontal thinned edges extracted in the left and right images. At first, nonhorizontal edge extraction is performed and thinned edge points are classified into two groups, positive and negative, depending on the gray-level difference between the two sides of the edge points in the x direction. The left and the right images are convolved with a proper gradient mask. To detect nonhorizontal edge points, we use a gradient of a two-dimensional Gaussian function with \( \sigma = 1 \) in the x direction as the gradient mask. This mask is truncated to \( 5 \times 5 \). A nonhorizontal thinned positive edge in the left image is localized to a pixel such that the filter response or \( \rho_+(x, y) \) has to exceed a positive threshold \( \rho^+_0 \) and has to obtain a local maximum in the x direction; therefore, [2]

\[
\rho_+(x, y) > \rho^+_0 \quad \text{Threshold.}
\]

\[
\rho_+(x, y) > \rho_+(x - 1, y) \quad \text{Local maximum.}
\]

### 5.1. Successive Connected Edge Points

Some connected edge points in the left image can be grouped together, thus forming sets that we call successive connected edges (SCE) sets. Each SCE set \( \Psi \) consists of \( n \) successive edges, \( \Psi = \{ p^l_1, p^l_2, p^l_3, \ldots, p^l_n \} \).

Its coordinates and type identify each edge point as \( p^l_k, p^l_k = (x^l_k, y^l_k, \text{type}) \). The set \( \Psi \) is called a successive connected edges set if these three conditions are met:

1. the types of all \( p^l_k \) are the same;
2. the successive \( p^l_k \)'s are in successive scan lines;
3. the absolute difference between \( x \) values of two successive points is less than 3, so we have \( x^l_{k+1} - x^l_k = \{-2, -1, 0, +1, +2\} \).

### 5.2. Search Space in the Edge Matching

Suppose that we want to find the correspondences of the edge points of a sample SCE set in the left image. Considering the \( d_a \) range and the connectivity of the edge points in a SCE set, if the value of \( \Delta x_l \) is known, the \( \Delta x_r \) range can be computed directly by a proper table (for example, Table 4 for \( \Delta x_l = 0 \) and Table 5 for \( \Delta x_l = +1 \)).

For example, consider \( p^l_{i-1} \) and \( p^l_i \) as two successive edge points in a sample SCE set and \( A_R \) as the correspondence of \( p^l_{i-1} \) in the right image (see Figs. 3a and 3b). Considering Eq. (3), \( \Delta x_l \) is the difference between the \( x \) position of \( p^l_i \) and \( p^l_{i-1} \) in the left. For finding \( B_R \) (the correspondence of \( p^l_i \) in the right image, the search space region or \( \Delta x_r \) range can be computed by the mentioned tables. This search region in the right image is shown in Fig. 3b. \( X^r_{\text{Range}} \) is considered the search space in the right image coordinate system and can be computed as

\[
d = x^l_{i-1} - x^r_A \Rightarrow \Delta x^r_{l} = \Delta x_r + (x^l_{i-1} - d). \quad (10)
\]

\[
\Delta x_r = x^r_A - X^r_{\text{Range}}
\]

In Fig. 3, \( \Delta x_l \) is considered to be \(-1 \) and, if \( d_{\text{max}} < 380 \), then the \( \Delta x_r \) range is \( \{-5, -4, -3, -2, -1, 0, +1\} \);
therefore, the search region is restricted to 7 pixels only. The search region is also shown in Fig. 3b. If $d_{\text{max}} < 170$, then the $\Delta x$ range is only $\{-2, -1, 0\}$. See Table 3 for the case of $\Delta x = +1$; the case $\Delta x = -1$ is similar in the negative direction.

5.3. SCE Set Construction and Matching

In the process of the edge matching, the edge points of the left image are divided into two groups, checked and unchecked edge points. The checked edges are those edge points that were already examined in the process, and the unchecked edges are those that have not been examined yet. In the following edge matching strategy, both the SCE set constructing the edge points of the left image and that establishing the correspondence are implemented concurrently. At first, all of the points in the left image are marked as unchecked. The proposed matching strategy can be briefly expressed in two phases as follows.

Phase 1.

Find the next unchecked edge in the left image by systematic scan, from the left to right and from the top to bottom. The found edge is considered as $p_i^{l}$, the first point of the corresponding SCE set. Consider $X_{\text{Range}}^{r}$ in the right image coordinate as the full search region based on the epipolar line and other constraints, and set $i = 1$. Go to Phase 2.

Phase 2.

1. Find the correspondence of $p_i^{l}$ in the right image, $B_{R}$, (see Fig. 3b) based on $X_{\text{Range}}^{r}$ and mark $p_i^{l}$ as checked edges. If $B_{R}$ is found, go to Step 2, else go to Phase 1.

2. Compute $d = x_i^{l} - x_i^{r}$ (Eq. (3)), and go to Step 3.

3. Find $p_{i+1}^{l}$, the next point of $p_i^{l}$ in the corresponding SCE set based on the three conditions of SCE sets (see Subsection 5.1), and go to Step 4. If $p_{i+1}^{l}$ is not found, go to Phase 1.

4. Compute $\Delta x_{i} = x_{i+1}^{l} - x_{i}^{l}$ (Eq. (4)), and go to Step 5.

5. Compute $\Delta x_{r}$ range, considering the mentioned tables, and then go to Step 6.

6. Compute $X_{\text{Range}}^{r} = \Delta x_{r} + x_{i-1}^{l} - d$ (Eq. (10)), and go to Step 7.

7. Set $i = i + 1$, and go to Step 1.

5.4. The Overall Algorithm (Matching Strategy)

The search space reduction is very important for decreasing the processing time of the matching. In the proposed SCE set construction and matching strategy, from the second point up to the end point of SEC sets, we could effectively reduce the search space for establishing the correspondence. On the other hand, considering a SEC set in the left image as $\Psi = \{ p_1^{l}, p_2^{l}, p_3^{l}, \ldots, p_n^{l} \}$, the search space can be reduced for the points of $p_i^{l}$, $i = 2, 3, \ldots, n$; however, for the first point that is found in the first phase of the proposed matching strategy, i.e., $p_1^{l}$, we employ the conventional multiresolution technique using the Haar wavelet [5] to reduce the search region. We use three levels of the Haar wavelet (original plus two of lower resolution). We use the normalized cross correlation (NCC) with a window size of $11 \times 11$, $13 \times 13$, and $15 \times 15$ for the coarse, medium, and fine levels, respectively. In the coarsest level, the search space is selected by considering the maximum of the disparity. At the higher resolution levels, the search space is cut around each found maximum correlation location in the previous level, $\pm 7$ pixels along the epipolar line. At the highest resolution, only similar edges on the epipolar line of the other image are examined.

For the second point up to the end point of the SEC sets, considering the relationship between disparities $\Delta x_{i}$ and $\Delta x_{r}$, we showed that the search region could be reduced. If the disparity search range can be automatically reduced to an effective range (about 10 pixels or less), then several local maximums would stay out of the selection process and, therefore, the disparities found would be correct, even if the size of the matching block is small [13]. Therefore, we can use a NCC with a window size of even $3 \times 3$ in the restricted search region.

Therefore, our algorithm employs the multisolution technique using the Haar wavelet to reduce the search region for the first point of a SCE set and then using the restricted search region based on the mentioned relationships.

![Fig. 3. An example of the search space in the edge matching. (a) Part of a sample SCE set in the left image, $p_{i-1}^{l}$ and $p_i^{l}$ are two successive edge points, and $\Delta x_l$ is the difference between their $x$ positions. (b) The search region for finding $B_{R}$ is shown as the $\Delta x_l$ range, and the epipolar line for $B_{R}$ is also shown with a dotted line.](image)
6. IMPLEMENTATION RESULTS

For comparing the results of the execution time and accuracy, we choose a multiresolution method based on the Haar wavelet as a reference. This method is based on the matching of the first point of the SCE set in the proposed algorithm. The feature points used in the reference algorithm, as well as in our algorithm, are non-horizontal edge points. We implemented and tested the proposed algorithm and the reference one for CIL Castle images at CMU [12], as shown in Fig. 4. The maximum of the disparity in these two images is around 110 pixels ($d_{\text{max}} = 110$), which is the highest disparity in this set; therefore, we consider the disparity range between 0 to 110 pixels.

We implemented and tested the proposed algorithm and reference one. The codes of the algorithms were written by Watcom C and implemented by a PC under the Windows operating system with a Pentium II 450 MHz processor. At the feature point extraction stage, 4963 nonhorizontal edges were found. The results of matching are shown in Table 6, which presents the number of matched points, the error points, the execution time, and, finally, the speed up. The values of the speed-up columns are given with respect to the reference algorithm.

The execution time of the feature point extraction stage is about 0.11 s. The matching stage is executed in 0.66 s for our algorithm and 1.11 s for the reference one. The execution time of our algorithm is about 1.58 times faster than the reference one, and, moreover, the error is less. In other words, the matched points are a little higher than the reference one: 2090 (42.1%) with respect to 1995 (40.2%) points.

The number of matched points in the two methods is not high, because some details are deleted in the coarser level of pyramid images and, thus, the matching cannot be established by multiresolution method. In the proposed method, 403 edge points from 2090 matched points are matched as the first point of SEC sets by the multiresolution method and 1687 edges points are matched as the second points up to end points of SEC sets in the restricted search region. As the first points of

Fig. 4. The Castle stereo images as test images for the proposed algorithm and the reference one: (a, b) left and right images; (c, d) the edge points of the left and right images. The positive edges are darker than the negative edges. The disparity maps are shown in (e) for the reference method and in (f) for the proposed one.
for the first point of SCE sets. It is better to use methods with a lower rate of failures matching applications, such as stereo robot vision. For the algorithm can be used in some fast edge-based stereo matching. We proposed a fast edge-based stereo matching algorithm based on the proposed search space reduction. Considering the traditional multiresolution algorithm using the Haar wavelet to reduce the search space in the edge-based stereo matching. We proposed a fast edge-based stereo matching algorithm based on the proposed search space reduction. Considering the traditional multiresolution algorithm using the Haar wavelet, our algorithm is 1.58 times faster and the error and the matching failures are also lower. Therefore, this algorithm can be used in some fast edge-based stereo matching applications, such as stereo robot vision. For improving the performance of the proposed algorithm, it is better to use methods with a lower rate of failures for the first point of SCE sets.

### 7. CONCLUSIONS

Considering the matching of edges in stereo correspondence, we could establish the relationships between the displacements of successive edges, the disparity under consideration, and the focal length. We combined this new idea and the multiresolution technique using the Haar wavelet to reduce the search space in the edge-based stereo matching. We proposed a fast edge-based stereo matching algorithm based on the proposed search space reduction. Considering the traditional multiresolution algorithm using the Haar wavelet, our algorithm is 1.58 times faster and the error and the matching failures are also lower. Therefore, this algorithm can be used in some fast edge-based stereo matching applications, such as stereo robot vision. For improving the performance of the proposed algorithm, it is better to use methods with a lower rate of failures for the first point of SCE sets.

### REFERENCES


Payman Moallem. Born in 1970 in Tehran, Iran. Received his BSc degree in Electronics Engineering from Esfehan University of Technology, Iran, in 1992, and his MSc and PhD degrees, both in Electronics Engineering, from Amirkabir University of Technology (Tehran Polytechnic), Iran, in 1995 and 2003, respectively. Since 1994, has been with Iranian Research Organization, Science and Technology (IROST) working on topics such as parallel algorithms and hardware used in image processing, DSP based systems, visual target tracking, and robot stereo vision. Has worked at the Iranian Aerospace Industrial Organization (AIO) and Esfehan University, both in Iran, since 1999 and 2003, respectively. His interests include fast stereo vision, robot vision, target tracking, real-time video processing, image recognition, and neural networks. Author of more than 25 scientific papers. Member of IEICE.

Karim Faez. Born in Semnan, Iran. Received his BSc degree in Electrical Engineering from Tehran Polytechnic University in 1973 and his MSc and PhD degrees in Computer Science from the University of California at Los Angeles (UCLA) in 1977 and 1980, respectively. A professor of Electrical Engineering at Amirkabir University of Technology (Tehran Polytechnic) in Iran. The founder and first chairman of the Computer Engineering Department of Amirkabir University (1989–1992). Chairman of the planning committee for Computer Engineering and Computer Science of Ministry of Science, Research, and Technology (1988–1996). His research interests include pattern recognition, image processing, neural networks, signal processing, Farsi handwritten processing, earthquake signal processing, fault tolerant system design, computer networks, and hardware design. Published more than 130 papers. Member of IEEE, IEICE, and ACM.