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DETECTION OF DOMINANT PLANAR SURFACES IN DISPARITY IMAGES BASED ON RANDOM SAMPLING

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Original scientific paper

In this paper, the applicability of RANSAC-approach to planar surface detection in disparity images obtained by stereo vision is investigated. This study is specially focused on application in indoor environments, where many of the dominant surfaces are uniformly colored, which poses additional difficulties to stereo vision. Several simple modifications to the basic RANSAC-algorithm are examined and improvements achieved by these modifications are evaluated. Two simple performance measures for evaluating the accuracy of planar surface detection are proposed. An experimental study is performed using images acquired by a stereo vision system mounted on a mobile robot moving in an indoor environment.

Keywords: *image segmentation, planar surface detection, RANSAC*

Detekcija dominantnih ravnih površina na slikama dispariteta na temelju slučajnog uzorkovanja

Izvorni znanstveni članak

U ovom članku ispituje se praktična primjenjivost RANSAC-pristupa za detekciju ravnih površina na slikama dispariteta dobivenim pomoću stereo vizije. Težište istraživanja je primjena u interijerima, gdje je velik dio dominantnih površina jednolično obojen, što predstavlja poseban problem za stereo viziju. Ispitano je nekoliko jednostavnih modifikacija osnovnog RANSAC-algoritma s ciljem utvrđivanja koliko oni mogu poboljšati njegovu učinkovitost. Predložene su dvije jednostavne mjere točnosti rekonstrukcija ravnih površina. Provedeno je eksperimentalno istraživanje na slikama snimljenim sustavom stereo vizije montiranom na mobilnog robota koji se kretao hodnicima fakulteta.

Ključne riječi: *detekcija ravnih površina, RANSAC, segmentacija slike*

1 Introduction
Uvod

Robots in the near future will be expected to operate autonomously in unstructured environments. In order to reach a required level of autonomy, a highly developed environment perception is necessary. Most mobile robots today are constructed to move in an indoor environment on a flat horizontal surface called herein the *floor surface*. Furthermore, other dominant surfaces in indoor environments, such as walls, doors, cupboard surfaces, etc. are planar or approximately planar. Hence, detection of planar surfaces can be very useful in robotics e.g. for motion planning, obstacle avoidance, determining the inclination of the camera, i.e. the camera pose relative to the gravity axis, or identification of planar surfaces of special interest for a particular transportation or object manipulation task. The topic of this paper is the problem of detection of dominant planar surfaces in disparity images obtained by stereo vision.

The plane in which the floor surface lies is referred to in literature as the *ground plane*. Several methods for ground plane detection have been reported. In, the ground plane is detected using the assumption that most of the points in the bottom part of the image represent the ground surface and that the stereo base is approximately parallel to the ground plane. Specific ground points are selected and the angle between the optical axis of the camera and the ground plane as well as the height of the camera relative to the ground plane are then computed using these points.

Alternatively, ground plane detection can be performed using v-disparity image. An assumption of this approach is that the rotation of the camera around its optical axis is negligible. Ground plane estimation by applying RANSAC to data obtained by stereo vision is reported in [3] and [4]. RANSAC [5] is a very popular method widely used in robotics to fit a model to a set of data corrupted by outliers. This approach is studied also in this paper.

Besides the floor surface, we are interested in the detection of other dominant planar surfaces in the robot's environment such as surfaces of stairs and walls. In, plane segments are extracted from disparity images using a Randomized Hough Transformation method and used for motion planning of a walking robot.

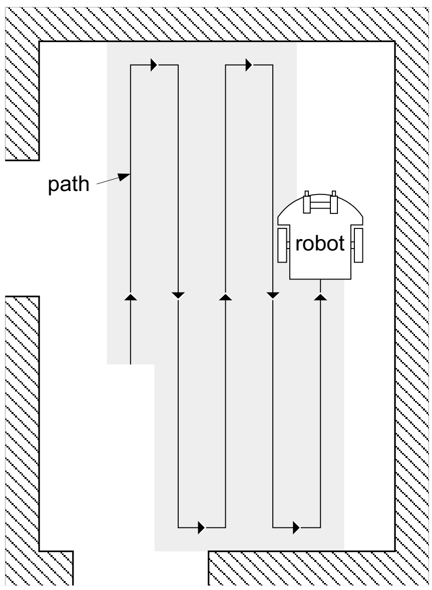

***Figure 1** A mobile robot covering a floor surface*
***Slika 1.** Mobilni robot prelazi površinu poda*

Furthermore, reconstruction of walls can be useful in mobile robot navigation. Let us, for example, consider an application where a mobile robot has a task to cover a given floor surface while performing an operation such as vacuuming, cleaning, grinding, etc., as shown in Fig. 1. In such an application, it is important for the robot to be able to move along a straight line during a certain period of time. One way to achieve this is to keep a constant orientation and distance relative to a wall surface.

The problem of detection of dominant planar surfaces considered in this paper is similar to the range image segmentation problem [7]. However, in comparison to the range images obtained by 3D laser range finders or time-of-flight cameras, disparity images provided by stereo vision systems are in general much more corrupted by outliers due to the ambiguity of stereo matching and often have large 'holes' corresponding to the surfaces in the scene which cannot be reliably reconstructed e.g. due to the lack of texture.

Standard stereo matching algorithms are local area-based (correlation) methods which make use of the color or intensity values within a finite window to determine the disparity for each pixel. Typically, these methods are simple and fast. However, they are often unreliable in homogenous regions and can be unreliable in textured regions if the window size is chosen incorrectly. Global area methods, on the other hand, determine all disparities for each pixel simultaneously by defining and minimizing an energy or cost function over the whole disparity map. These methods achieve a higher degree of accuracy in retrieving disparity information. They perform better in homogenous regions but frequently have parameters which are difficult to set and are computationally expensive. Belief Propagation [8] is presently a popular global area method employed in stereo matching algorithms. Current state-of-the-art methods combine region (or segment) based methods with global area methods such as belief propagation [9, 10], or cooperative optimization [11]. Region based methods are based on the assumption that depth (disparity) changes occur at region boundaries in the image so the image is first segmented and then the segments are matched. Thus, a disparity plane is assigned to each segment instead of assigning a disparity value to each pixel. As a result, the scene is modeled by a set of planar surface patches.

The discussed stereo reconstruction approaches provide detailed 3D scene reconstruction in times ranging from 15 s to 35 s for the same test image. Various real-time or near real-time stereo vision systems have also been reported. In [12], an approach is reported which gives near real-time results by employing a local area-based method through an efficient segmentation-based cost aggregation strategy. Real-time results are achieved in [13] by implementing a line segment based stereo correspondence algorithm using tree dynamic programming. In [14], real-time results are obtained by implementing a belief propagation based global algorithm in a graphical processing unit. These approaches report speeds ranging from 16 ft/s to 1,2 ft/s. On the other hand, these methods do not give as accurate results as do the methods presented in [9, 10] and [11], where accuracy is typically achieved at the expense of computation efficiency.

The focus of this paper is on the fast detection of few most significant planar surfaces in the robot's environment for robotic applications where the reconstruction of small structures and precise delineation of surfaces is not critical.

In this paper, application of RANSAC for the detection of dominant planar surfaces in disparity images obtained by stereo vision and estimation of their parameters is considered. Several modifications to the basic RANSAC-algorithm are examined and improvements achieved by these modifications are investigated. Two main properties are of interest, the computational efficiency, which is critical for real-time applications and the accuracy of estimation of the plane parameters, which directly influences the navigation performance.

The images used for experimental evaluation of the algorithms proposed in [9, 10, 11] represent either scenes with many small surfaces or surfaces rich in texture. For such scenes stereo reconstruction is expected to give good results. On the other hand, this study is specially focused on applications in indoor environments, where many of the dominant surfaces are uniformly colored, thereby posing additional difficulties to stereo vision.

In the next section, the basic RANSAC-approach for the detection of planar surfaces is described. Few modifications to this basic approach are discussed in Section 3. An experimental study of these modifications is presented in Section 4. The experiments are performed using a stereo camera system mounted on a mobile robot. Two performance measures are used as benchmarks, the accuracy of estimation of the angle between the floor surface and the dominant wall surface in the considered scene and the accuracy of estimation of the line representing the intersection between these two surfaces.

2 RANSAC-approach to detection of planar surfaces
Detekcija ravnih površina RANSAC-pristupom

In this section, the case is considered where one or more planar surfaces are present in a scene observed by a stereo camera system consisting of two cameras, the left and the right one. An algorithm for dense stereo reconstruction, such as the one presented in [15], provides a *disparity image* of an observed scene. A disparity image can be regarded as a set of points in the *disparity space, each represented by a vector* $\boldsymbol{q} = [u, v, d]^{\mathrm{T}}$, where u and v are the coordinates of a left camera image point and d is the disparity assigned to this point by a stereo reconstruction algorithm. Each image point represents the image projection of a point on a surface in the observed scene and the disparity value assigned to this point provides the information about the distance of this point relative to the camera system. From vector $\boldsymbol{q}$ and the parameters of a calibrated stereo camera pair, the coordinates of the point relative to the camera coordinate system can be computed.

Let A be the set of all points reconstructed by stereo vision. It can be easily shown that a plane in a Euclidean 3D space maps to a plane in the disparity space [17, 18]. Therefore, in the case where one or more planar surfaces exist in an observed scene, set A contains one or more subsets of approximately coplanar points. In the ideal case, coplanar points satisfy the relation

$$au + bv + c = d,$$

where $\boldsymbol{l} = [a, b, c]^{\mathrm{T}}$ represents the vector of parameters of the plane on which these points lie. In a real situation, the points $\boldsymbol{q}$ corresponding to a set of coplanar 3D points in the scene are not ideally coplanar due to imperfectness of the image acquisition and stereo reconstruction. Therefore, planar structures in the scene would correspond to sets of approximately coplanar points $\boldsymbol{q} = [u, v, d]^{\mathrm{T}}$ which satisfy

$$au + bv + c - d \leq \varepsilon, \tag{1}$$

where ε is a small value. The value

$$r(\boldsymbol{q},\boldsymbol{l}) = au + bv + c - d$$

is referred to herein as the *residual* of the point $\mathbf{q}$ with respect to the plane $\boldsymbol{l}$.

A *dominant planar surface* is a planar surface in the scene which corresponds to a relatively large number of image points. Detection of a dominant planar surface can be performed by searching for a large set B of approximately coplanar points. The remaining points in A are considered to be outliers for that surface. One approach which can be used for that purpose is the RANSAC paradigm [5]. Application of RANSAC for ground plane detection in disparity images is proposed in [3]. The detection of dominant planar surfaces based on this approach can be implemented by Algorithm 1.

Algorithm 1 Basic RANSAC-algorithm for detection of planar surfaces

Input: A, ε, $t_{\max}$
Output: $\boldsymbol{l}^*$, B^*
$s^* \leftarrow 0$
$t_0 \leftarrow t$
repeat
Randomly select 3 points $\boldsymbol{q}_j$, $\boldsymbol{q}_k$ and $\boldsymbol{q}_l$ from A.
Determine the parameters $\boldsymbol{l} = [\,a, b, c\,]^{\mathrm{T}}$ of the plane containing the points $\boldsymbol{q}_j$, $\boldsymbol{q}_k$ and $\boldsymbol{q}_l$.
Let B be the set of all points $\boldsymbol{q} = [u, v, d]^{\mathrm{T}} \in A$ which satisfy (1) for the given $\boldsymbol{l}$.
if $s(B, \boldsymbol{l}) > s^*$ **then**
$s^* \leftarrow s(B, \boldsymbol{l})$
$B^* \leftarrow B$
end if
while $t - t_0 < t_{\max}$
Determine the parameters $\boldsymbol{l}^*$ of the plane representing the best least-squares fit to the points in B^*.

Three points are randomly selected from A. These 3 points define a plane. Let this plane be represented by parameter vector $\boldsymbol{l} = [a, b, c]^{\mathrm{T}}$. The set of all points $\boldsymbol{q} \in A$ lying on that plane within tolerance ε is referred to as the *consensus set*. The more points a consensus set contains, the higher is the probability that it represents a planar surface. The plausibility of the hypothesis that a planar surface defined by parameters $\boldsymbol{l}$ exists in the scene can be evaluated by an *objective function* $s(A, \boldsymbol{l})$ which assigns higher values to more probable hypotheses. This random sampling procedure is repeated for a certain number of times and the consensus set B^* corresponding to the highest value $s(A, \boldsymbol{l})$ is considered to be the dominant approximately coplanar subset of A. The parameters of the surface represented by set B^* can be computed e.g. by least-squares fitting of a plane to the points $\boldsymbol{q} \in B^*$. The number of random samples needed to reliably detect a dominant planar surface can be computed as proposed in [5]. However, in real-time applications it is appropriate to limit the execution of the algorithm to a predefined time $t_{\max}$. Algorithm 1 represents such a time-limited RANSAC procedure.

Differentiating the points belonging to a planar surface from other points depends crucially upon the tolerance ε. Various methods for selecting this tolerance based on statistics of the residuals have been proposed [19, 20, 21].

3 Segmentation of disparity image
Segmentacija slike disapariteta

Detection of dominant planar surfaces using stereo vision can be regarded as the segmentation of the disparity image into regions, where each region represents a planar surface in the observed scene. These regions are referred to in the following as *segments*. Algorithm 1 described in Section 2 can be used to detect the dominant planar surface in set A of points reconstructed by stereo vision. If the points belonging to that surface are removed from A and Algorithm 1 is applied to the obtained point set, the second dominant planar surface in the scene can be detected. This procedure can be repeated until all significant planar surfaces are detected. This approach is commonly applied for range image segmentation [19, 20, 21]. In the following, application of this strategy to segmentation of disparity images is discussed.

The quality of segmentation can be improved by making certain assumptions about the structure of the scene. It can be expected that in most cases a surface in the scene is represented by a connected set of points in the image. Hence, it is a common approach to require that the segments are connected subsets of A. However, in the case of a poorly textured surface, it can happen that many points representing that surface in the image cannot be reconstructed by stereo vision, resulting in large gaps in the obtained disparity image. Three sample disparity images are shown in the second row of Fig. 3. The lighter points have greater disparities i.e. are closer to the camera. The black points represent the points which could not be assigned a disparity due to stereo ambiguity. Notice that the floor surface contains many gaps. As the result, it can be expected that a floor surface is often represented by a disconnected set of points in disparity image, although the same surface represents a connected point set in the original camera image shown in the first row of Fig. 3. In order to allow surfaces to be detected as connected regions, the gaps in disparity images can be filled by dilation of the reconstructed regions in the disparity image by an appropriate structural element.

Algorithm 2 Detection of dominant planar surfaces in disparity image

Input: A, $n_{\min}$
Output: $\Re$
Determine the connected components of A. Let Ξ be the set of connected components of A with at least $n_{\min}$ points. Elements of Ξ are sets of points.
$\Re \leftarrow \varnothing$
repeat until $\Xi = \varnothing$
$C \leftarrow$ the greatest element of Ξ
Detect the dominant planar surface in C using Algorithm 1. Let $\boldsymbol{l}$ be the vector of parameters of the dominant planar surface.
$B \leftarrow$ set of all points $\boldsymbol{q} \in C$ which satisfy (1).
$C_B \leftarrow$ the greatest connected component of B.
if $|C_B| \geq n_{\min}$ **then** insert C_B into $\Re$.
Remove C from Ξ.
Determine the connected components of C/C_B with at least $n_{\min}$ points and insert them into Ξ.
end repeat

Furthermore, if only dominant surfaces are of interest, then the segmentation algorithm can be designed to detect only surfaces which are represented in the image by segments of at least n_{min} points, where n_{min} is a predefined threshold value, while smaller segments are considered insignificant.

Algorithm 2 presented in the following segments a point set A into connected subsets of approximately coplanar points, where each segment includes at least n_{min} points. A similar algorithm is used in [21] for range image segmentation.

The most computationally demanding step of Algorithm 2 is the RANSAC-based detection of the dominant planar surface in a point set C (line 5). Its efficiency can be improved if a sub sampled set C is used instead of the full set. The subsampling is performed by considering only those points in C that lie on the sub lattice spaced by one in δ pixels horizontally and one in δ pixels vertically, as proposed in [21].

Figure 2 *Mobile robot Pioneer 3DX equipped with a stereo camera system Videre design STH DCSG-STOC.*
Slika 2. *Mobilni robot Pioneer 3DX opremljen sustavom stereo kamera Videre design STH DCSG-STOC.*

4 Experimental results
Rezultati pokusa

In this section, an experimental study of the applicability of the RANSAC-based disparity image segmentation algorithm discussed in Sections 2 and 3 for detection of dominant planar surfaces in poorly textured indoor scenes is reported. The experiments are performed by applying the considered approach to disparity images obtained by a correlation based algorithm, Small Vision System (SVS) [15]. The disparity images are created from image pairs taken by a stereo camera system Videre design STH DCSG-STOC mounted on a mobile robot Pioneer 3DX shown in Fig. 2 while the robot was moving in an indoor environment. After removing image sequences corrupted by motion blur, a total of 47 stereo image pairs were obtained. Three sample images taken by the left camera are shown in the first row of Fig. 3 and the corresponding disparity images are shown in the second row of Fig. 3. Algorithm 2 is then applied to detect the dominant surfaces in the disparity images obtained by SVS. As the result, a set of planar surfaces is detected in each disparity image. Only the surfaces represented by at least $n_{min} = 1000$ points are considered. The surfaces are classified as steeply and gently sloped surfaces. The gently sloped surface supported by the highest number of points in a disparity image is considered to be the floor surface.

Two modifications to Algorithm 2 are investigated in this paper:

- *A* subset of C obtained by subsampling with $\delta = 5$ was used in step 5 instead of the full set;
- Small gaps in the disparity images were filled by dilation of connected regions in order to allow surfaces to be detected as connected regions. The dilation of each region is performed by adjoining image points in 4-neighborhood of region boundary points to the region and repeating this procedure 5 times.

The tolerance ε, used in the basic RANSAC algorithm to distinguish inliers from outliers is set to an empirically determined value of 1 pixel. A method which enables the automatic selection of tolerance ε referred to as RESC is proposed in [19]. The RESC algorithm was also implemented in order to investigate whether this approach to automatic selection of tolerance can improve image segmentation significantly in the considered case study.

In the case of the standard RANSAC approach, the objective function $s(A, \boldsymbol{l})$ used for hypothesis evaluation is the number of points from set A lying on the plane defined by parameters $\boldsymbol{l}$ within tolerance ε, while in the case of RESC-based surface detection, the objective function proposed in [19] is used. In the RESC-based algorithm, only the points $\boldsymbol{q}$ for which the residuals are lower than 5 pix are considered as candidates for inliers. All the other parameters of the RESC-algorithm are set to the same values as in [19]. Furthermore, tolerance ε is computed using the improvement to the original RESC-method proposed in [21]. In the experimental evaluation presented in this section, the RESC-approach is used in combination with both subsampling and dilation.

The execution time was limited to $t_{max} = 0{,}02$ s per surface for all methods. The evaluated algorithms were executed on a PC with a 3,40 GHz Intel Pentium 4 Dual Core CPU with 2 GB of RAM.

In the case where both subsampling and dilation were applied, the floor surface was detected in all 47 stereo images, while in the case where dilation was not applied, the floor detection failed once. Furthermore, in the case where dilation was not applied, the floor surface was detected as 2 or more separate surfaces in 20 stereo images, while the algorithm with dilation accomplished to merge these surfaces into a single floor surface. An example of this effect is shown in Fig. 4.

In order to evaluate the accuracy of the plane parameter estimation, the estimated values of parameters a, b and c of the reconstructed planar surfaces should be compared to ground truth, i.e. the true value of these parameters. Determining these true values would assume precise measurement of the position and orientation of the considered planar surfaces relative to the camera system. Such measurements are, however, very difficult to obtain. Therefore, we propose two performance measures which can be easily computed. First is the angle between the floor surface and the dominant wall surface referred to herein as θ_π. Since the walls in the environment considered in our experiments are vertical, this angle is 90°. The floor surface and the dominant wall surface detected in 3 sample images are shown in the third row of Fig. 3. The second performance measure indicates the accuracy of the estimated direction of the line representing the intersection

***Figure 3** Images taken by the left camera mounted on a mobile robot (first row); the corresponding disparity images (second row); the result of the image segmentation (third row): detected floor surface (white) and the dominant wall surface (black) and performance index (last row): GT line (white) and the reference line (black).*

***Slika 3.** Slike snimljene lijevom kamerom pričvršćenom na mobilnog robota (prvi red); slike dispariteta dobivene iz stereo para slika (drugi red); Rezultat segmentacije slike (treći red): detektirana površina poda (bijelo) i dominantna površina zida (crno) te mjera učinkovitosti (posljednji red): GT linija (bijelo) i referentna linija (crno)*

***Figure 4** In the case where dilation is not applied, two surfaces are detected corresponding to the floor surface. These surfaces are represented by the black and white region in the left image. In the case where dilation is applied, these two surfaces are merged into a single floor surface represented by the white region in the right image.*

***Slika 4.** Kada proširenje nije primijenjeno, pod je detektiran kao dvije površine predstavljene bijelim i crnim područjem na lijevoj slici. Kada je primijenjeno proširenje, ove dvije površine su spojene u jednu površinu predstavljenu bijelim područjem na desnoj slici* of the floor and the dominant wall surface. This line is important since it can be used in navigation of a mobile robot. For example, if a robot has the task to cover a given surface by moving along straight paths as shown in Fig. 1, it could perform such a task by following a wall, i.e. by moving parallel to the line representing the intersection of the floor and wall surface. This line is referred to in the following as the *reference line*. In the analysis reported in the following, the accuracy of estimating the direction of the reference line is assessed by comparing the estimated reference line direction to the direction of the manually specified *ground truth* (GT) line, such as the one shown in the fourth row of Fig. 3. The directions of these two lines can be compared in two ways, by comparing their image projections and by comparing their directions in 3D. The direction of the GT line in 3D is obtained by projecting the manually specified line onto the floor surface estimated by Algorithm 2. Although the accuracy of both the 3D GT line and the reference line depends on the accuracy of the floor surface estimation, the difference between the directions of these two lines is expected to provide a rather good assessment of the reconstruction precision. The difference between the directions of the image projection of the reference line and the GT line is denoted herein by θ_{2D} and the difference between these two lines in 3D by θ_{3D}.

Since RANSAC is a randomized algorithm and can give a different result for the same input data each time it is applied, an experiment was performed by applying the considered algorithms to the acquired stereo image sequence 11 times in order to obtain better statistics. The results obtained are displayed in Fig. 5. The performance measures are represented by normalized cumulative histograms[1)].

Subsampling has shown to have a significant impact to the algorithm performance. It allows more hypotheses to be posed in the same amount of time in comparison to the case without subsampling. A greater number of hypotheses increase the probability of making a good hypothesis.

***Table 1** Maximum angle errors in 99 % of the trials*
***Tablica 1.** Najveće pogreške u određivanju kuta u 99 % slučajeva*

	subsampling + dilation	subsampling	dilation	RESC
θ_π / °	15,39	17,01	30,66	43,15
θ_{2D} / °	4,99	5,19	13,98	17,33
θ_{3D} / °	12,85	13,66	25,46	33,89

***Table 2** Standard deviation of the angle errors*
***Tablica 2.** Standardna devijacija pogreške u određivanju kuta*

	subsampling + dilation	subsampling	dilation	RESC
θ_π / °	3,90	3,78	6,87	7,50
θ_{2D} / °	1,32	1,41	4,15	2,51
θ_{3D} / °	3,37	3,85	6,36	5,21

1) Normalized cumulative histogram is a way of representing measurement data where the horizontal axis represents the measured variable x and the vertical axis the number of measurements $y(x)$ which are $\leq x$ divided by the total number of measurements. In this paper $y(x)$ is represented as percentage.

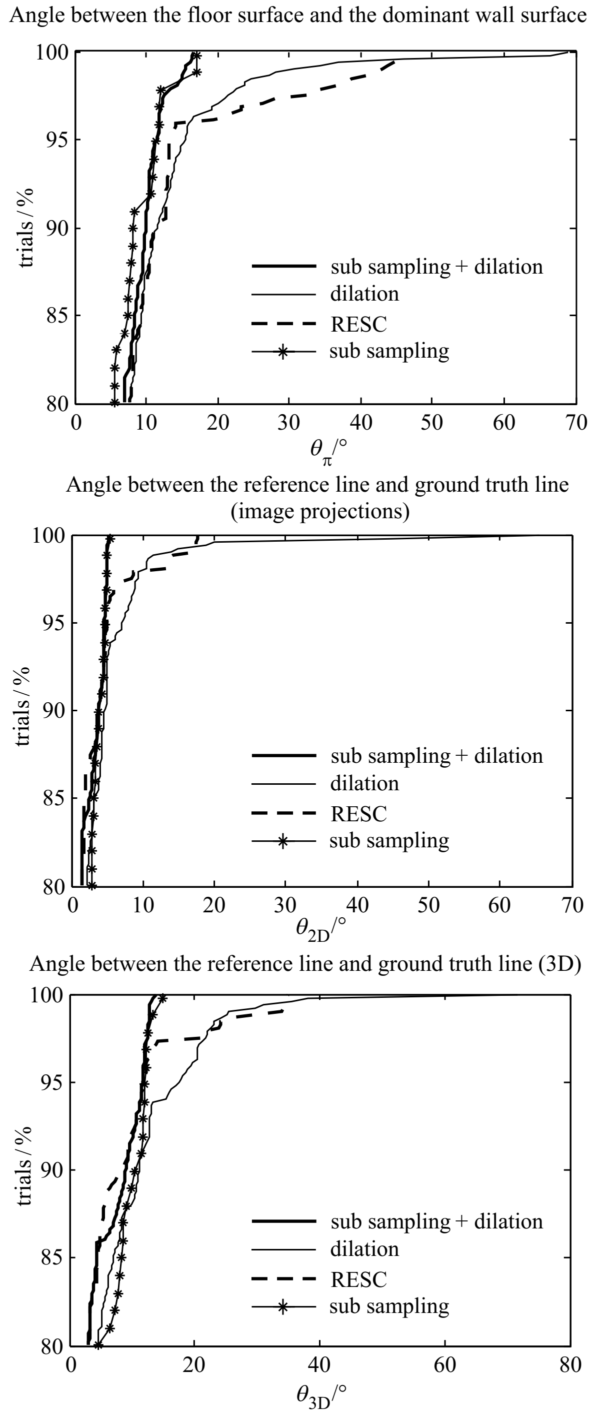

***Figure 5** Normalized cumulative histograms of the angle differences*
***Slika 5.** Normirani kumulativni histogrami razlike kutova*

Although the dilation step provided a better segmentation, it did not show to have a significant effect on the surface reconstruction accuracy.

For the considered case study, RESC-approach did not show a significant advantage in comparison to the standard RANSAC-approach.

Tab. 1 shows the maximum angle differences obtained in 99 % of the trials, while Tab. 2 shows the standard deviations of the angle differences for the implemented algorithms. It can be noticed that the maximum angle difference given by the algorithm with subsampling is approximately 2 times less than those obtained by the variant without subsampling and the RESC-approach in 99 % of the trials.

5 Conclusion
Zaključak

In this paper, the applicability of RANSAC-based disparity image segmentation algorithm for the detection of dominant planar surfaces in poorly textured indoor scenes is investigated. An experimental study of the considered approach is conducted in which the discussed algorithm is applied for the reconstruction of the most significant planar surfaces in images of indoor scenes. The images were taken by a stereo camera system mounted on a mobile robot. Two simple performance measures are proposed, the accuracy of estimation of the angle between the floor surface and the dominant wall surface and the accuracy of determination of the reference line representing the intersection between these two surfaces. The results of the reported experiments indicate that undersampling of data in plane detection step improves considerably the computational efficiency of the algorithm without having a significant impact on the accuracy of the plane parameter estimation. Furthermore, in the reported experiments, it often happened that the floor surface, which is of special importance, is represented in the disparity image by few separated regions due to lack of texture. Hence, dilation of regions in the disparity images is a highly recommendable preprocessing step in indoor applications, since it allows detection of large connected regions and larger data sets are expected to provide a more precise estimation of the surface parameters.

The determination and evaluation of the consensus set using the approach applied in RESC-algorithm did not show significant advantage in comparison to the standard RANSAC-approach. The advantage of RESC-algorithm over the standard RANSAC-approach is that it does not require a user defined threshold for discriminating outliers from inliers, but rather estimates this threshold from the given input data. Since we were interested in the detection of almost perfectly planar surfaces, we were able to estimate the appropriate value for the aforementioned threshold beforehand from the distribution of the sensor measurement noise only. Thus, our algorithm was at an advantage since it was given more or less correct information about the distribution of inliers which the RESC-algorithm had to estimate itself.

The RANSAC-based segmentation algorithm presented in this paper, executed on a standard PC-hardware, reliably detected dominant surfaces at the rate of 20 ms per surface. The standard deviation of the angle between the floor surface and the dominant wall surface was 3,90 and the error in estimating this angle was below 16 in 99 % of trials. The accuracy of determining the reference line which can be potentially used for robot navigation is estimated by comparing the direction of this line to the direction of manually specified ground truth. The difference of these two directions was below 13 in 99 % of trials and the standard deviation of this difference was 3,37.

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