Range image recognition based on statistical multiresolution approach

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Abstract: - This paper proposes a robust multiresolution approach to detecting the structure of a noisy range image. It is assumed that the original image, consisting of planar and quadratic surfaces, is corrupted by heavy noise composed of Gaussian background noise and impulse noise. A basic principle of our approach is the exploitation of the structure of scan lines for detecting the image structure. Thus, the main part of our algorithm is essentially one-dimensional, allowing a significant decrease in computational complexity. A new curve recognition technique based on multiresolution hypothesis testing is suggested. This technique allows us to take into account domain knowledge and to improve the efficiency of the method. Finally, a procedure for detection, recognition, and reconstruction of surface patches is introduced.

Key-Words: -Edge detection, multiresolution, range image, robust estimation

1 Introduction

Many object recognition algorithms using range images, since a range image provides geometric information about the object independent of the position, direction, and intensity of light source illuminating the scene. This paper deals with localization 3D objects and their recognition. The problem has a wide range of application like automated visual inspection of industrial parts or radar image analysis. The subject of our interest is an image corrupted by heavy noise composed of Gaussian background noise and impulse noise (outliers). Under such a situation, the problem of image understanding is almost unsolvable without some prior knowledge about the original structure. It is assumed that the real image is the corruption of an underlying piecewise smooth image with an unknown number of both planar and quadratic surface patches. This assumption does not severely restrict our problems because a wide class of real images can be approximated as a combination of these basic forms. Thus the work mainly concentrates on localization of smooth regions, corresponding to distinct smooth surfaces, and on recognition of their surfaces contaminated by composite noise.

Naturally, there are a lot of methods dealing with this problem. One of the classical approaches is the image segmentation. The problem is that the heavy composite noise prevents from the using of standard techniques. Thus, the methods, using the local operators (for edge detecting or for smooth regions restoring) are not able to cope with heavy noise, especially in the case when there are no jumps in depth function. Hence for structure detection it would be reasonable to use global information about the image, but many techniques using a global information (e.g. MRF models[6]) lead to algorithms of high computational complexity and, like the more fast methods based on a model selection [3], do not handle outliers.

In many works the problem of outliers is solved by a noise cleaning, but the different filters, removing impulsive noise tend to distort structures that are not monotone or linear. In our work, we introduce a novel outlier cleaning technique that detects and removes impulse noise only, but does not smooth non-impulse noise that allows keeping the image structure. Note, that no noise cleaning method ensures perfect outlier detection (especially when the magnitude of outliers is not much larger than the signal). Therefore, even after noise cleaning we should use methods which are robust enough to deal with the remaining outliers.

Another alternative is to use some robust methods [5], but many of these methods suffer from drawbacks in detecting the piece-wise structure [10], because highly robust statistical techniques are frequently found to be insensitive to the transitions between smooth regions, considering samples belonging to other regions as outliers for the given region.

Thus, the highly robust methods are insensitive to the changes of the depth function structure, and vice versa, the methods, sensitive to the piecewise structure is not robust. So, we need a new method, providing detection the piece-wise structure contaminated by heavy composite noise. It must be some combination of high sensitivity to changes in piecewise structure and robustness.

We propose a novel approach, which is based on the following principles:

- Our algorithm exploits the **structure of scan lines** for detecting the image structure. Thus, the main part of out algorithm is essentially one-dimensional. This approach allows significantly decrease the computational complexity and simultaneously use a global information of the image.
- The method for detecting the scan line structure is based on a procedure of **statistical hypothesis testing** which is sensitive to changes in signal structure and allows coping with outliers. The suggested approach allows to take into account domain knowledge and thus to construct the problem-oriented algorithm that drastically improves efficiency of the method.
- The **outlier detection** proceeds in two steps. In the preprocessing stage we apply an outlier cleaning technique that allows the percentage of outliers to be reduced from the initial situation of up to 25% to no more than 5%. The remaining outliers are handled by the algorithm for detecting scan line structure.

There are another works [8,9] based on scan line approximation technique. The main difference between these works and our approach is the method of partitioning each scan line into smooth regions. If the works [8,9] are based on the heuristic splitting algorithm from [7] improving by merging step ([9]), our method is based on a procedure of statistical hypothesis testing which is more precise, non-parametric and allows coping with heavy noise.

The main steps of our method are the following:

- **One-dimensional structure detection.** The set of edge-points and interior labels is obtained as follows: the real image is divided into rows and columns, and for each row (column) the *tree of possible approximations* is built by using a multiresolution procedure of statistical hypothesis testing; the optimal approximation is found as the minimal cost path of this tree; the interior points of regions are labeled according to the approximation, and with it the boundary of the regions are declared to be edge-points.
- **Two-dimensional structure detection.** The wrong labeling, caused by heavy noise, is corrected by using the geometrical properties (as boundary continuity and correlation between rows and columns). Some rough segmentation, as set of smooth regions interiors (support regions), is defined by final set of labels. The regions are classified based on domain knowledge, and parameters of approximating surfaces are robustly estimated for interested us models. Finally, the original image or some its parts are reconstructed.

The one-dimensional algorithm of image labeling, including the multiresolution procedure of statistical hypothesis testing, and outlier detection algorithm are described in Section 2. The image labeling algorithm is based on the signal analysis technique investigated in [1,4]. Here the technique is improved and extended to image analysis. Section 3 presents the two-dimensional structure detection algorithm and demonstrates experimental results.

2 One-dimensional image labeling

A range image is a 2D array of corrupted values of the underlying depth function *f*. A n x *n* range image is given by the value $Z(x,y)$ of a discrete function Z:

$$Z(x,y)=f(x,y)+\varepsilon_{xy},$$

where

$$f(x,y)=\sum_{i+j<3} a_{ij}x^i y^j$$

and ε_{xy} is a random variable from a complex noise.

A scan line of such image is a quadratic curve segment in the *x-z* (*y-z*) plane. Consider the problem of 1D signal structure detection. Let $X=[x_1,x_2,\ldots,x_n]$ be an array of n pixels (a row or a column), and $Z=[z_1,z_2,\ldots,z_n]$ be an array of n corrupted values of the underlying depth function f. We assume that value z has the form

$$z_i=f(x_i)+\varepsilon_i+\xi_i,$$

where ε_i is an i.i.d. Gaussian random variable $N(0,\sigma^2)$, and ξ_i is an i.i.d. random variable from an impulse noise. Our model of the impulse noise is the following: with a standard probability π impulse noise may appear in any point independently as an addition to the image value corrupted by background Gaussian noise; the addition may be positive as well as negative.

The preprocessing stage of our algorithm is outlier detection. To do this we need to distinguish between outliers and regular values of the image (inliers). The problem is that the regular values are not the values of the underlying function. They are also corrupted values, but only by Gaussian noise. Knowledge of the background noise (σ) allows us to detect outliers. To estimate σ the algorithm described in [2] may be used.

We propose a three-stage algorithm for outlier elimination. In the first stage, called *labeling*, each point is labeled as an outlier or an inlier. To distinguish between inliers and outliers we use the simple idea that an inlier z(x) has to be close to a line L passing through two nearby points and an outlier will be far from it, i.e., the null hypothesis that z(x) is inlier is accepted if two values z(x) and $L(x)$ are close $((|z(x)- L(x)|/\sigma)<\theta)$. Parameter θ was chosen in such a way that a maximum number of real outliers were detected, since in this stage we prefer to obtain false outliers (which will be detected on the second stage) rather than to miss real outliers. To improve the outlier detection we perform this test repeatedly for different triplets of points, keeping the central point fixed. The type of the point is determined according to some consensus rule.

On the first stage a large percentage of real outliers is detected, but at the same time a number (till 5%) of false outliers was included into the outlier set. The goal of the *correction* stage is to move them into the inlier set. Since most of the false outliers lie in the boundary layers, the one-side outlier test was used. The one-side test is similar to the test described in the previous stage, but nearby points is chosen from one side of the detected point.

On the last, *elimination*, stage we remove impulse noise and substitute the outlier value by the result of a line fitting to three neighboring inlier points.

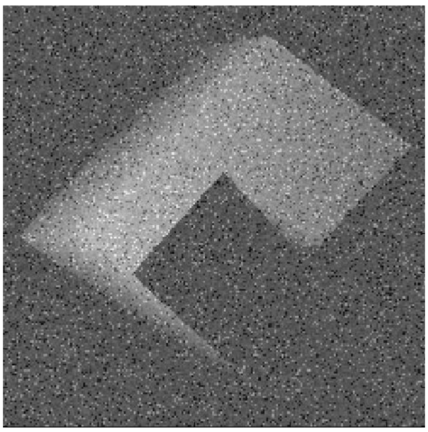

Fig.1 (a). Noisy image

We demonstrate in Fig. 1 (a,b,c,d) the outlier detection algorithm for the real range image corrupted by heavy Gaussian noise (σ = 10) with 15% outliers. We can see that not all outliers were removed, but the percentage of undiscovered outliers is less than 2%.

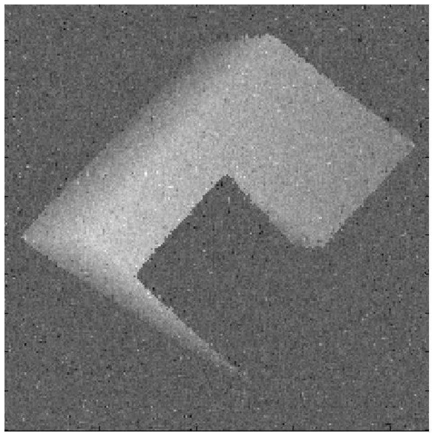

Fig. 1 (b). Cleaned image

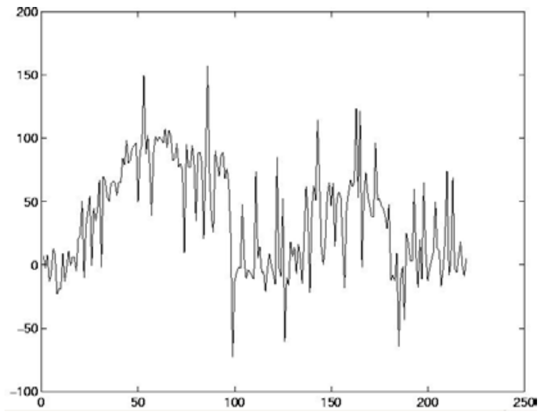

Fig. 1 (c). The 100th row of noisy image

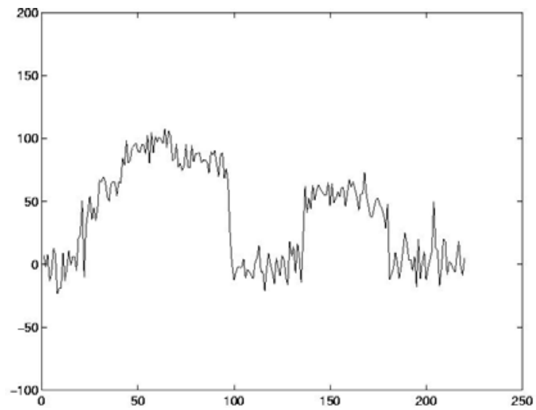

Fig.1 (d). 100th row of cleaned image

Polynomial curve identification is the main part of the algorithm. First, consider a curve segment, represented by a (k-1)-order polynomial corrupted only by Gaussian noise $N(0,\sigma^2)$. To estimate their parameters we take k sample pixels from the segment: $(x_1,z_1),\ldots,(x_k,z_k)$. If k=1 the leading coefficient $a_0= z_1$, if k=2 (line) then the leading coefficient $a_1=(z_1- z_2)/(x_1- x_2)$ and so on. Statistical estimation of the leading coefficient a_k has Gaussian distribution with zero mean and variance depending on the distances between x_i and x_j (i,j=1,2,…,k) and on the variance of noise σ^2. So, if $x_{i+1}-x_i=\Delta$ for each i=1,2,…,k-1, for the constant, linear, and parabolic dependences we obtain

$$\sigma^2_{const} = \sigma^2; \sigma^2_{lin} = \frac{2\sigma^2}{\Delta^2}; \sigma^2_{prb} = \frac{3\sigma^2}{2\Delta^4}.$$

Therefore, if we have a pattern of test pixels (PTP) and a shifted pattern the values of variances of the leading coefficients are the same and do not depend on the location of PTP. In this way we can obtain a set of i.i.d. estimates of leading coefficients. The scattering of the estimates may be evaluated by the variance estimate s^2. Thus by fixing a sets of PTP's we obtain n_{lin} and n_{prb} estimates for linear and parabolic case; for constant dependence the values of the function $z(x)$ play the role of such estimates. For each of these three sets of estimates the values s^2_{const}, s^2_{lin}, and s^2_{prb} are calculated. If the segment has a constant/linear/parabolic form corrupted by i.i.d. Gaussian noise with the given variance σ^2 then the corresponding expressions

$$\chi^2_{form} = \frac{(n_{form}-1)\, s^2_{form}}{\sigma^2_{form}},$$

where *form* is *const* or *lin* or *prb* corresponding, have a chi-square probability distribution with $(n_{const}-1)$, $(n_{lin}-1)$, $(n_{prb}-1)$ degrees of freedom, respectively. The three null-hypotheses concerning constant, linear and parabolic forms of dependence are checked independently and a given null-hypothesis is accepted if corresponding χ^2 not great than χ^2_α (where α is a pre-established significance level).

Now consider the optimal approximation of 1D signal corrupted by Gaussian noise and by impulse noise. To determine the first smooth region we consider the set of growing windows and for each one we independently test (by using the above-described algorithm) three null-hypotheses: the window may be approximated by a constant, a line or a parabola.

The rejection of any of these hypotheses at a particular point may be caused by two phenomena: (a) the presence of outliers inside the tested window (in this case the hypothesis is accepted on the tested window without some small cutting segment, then the window is extended and the basic algorithm is repeated) or (b) the change of the signal form.

As a result of the first stage we have the longest possible constant - $[x_1,x_{const}]$, linear - $[x,x_{lin}]$, and parabolic - $[x,x_{prb}]$ regions. The first stage is repeated from the pixel $x_{const}+1$ ($x_{lin}+1$, $x_{prb}+1$) and in this way a K-level tree of possible approximation is obtained.

Among all the possible approximations (K-paths on the tree) we select one of the "minimal complexity", which can be computed as

$$C_{total} = \sum_{i=1}^{K} c_i \Big/ \sum_{i=1}^{K} l_i$$

where c_i is the complexity of the i-region, and l_i is the length of this region. The complexities of a constant, linear and parabolic region were taken as 1, 1.75, and 2.5 respectively. The reason for this weight assignment is to favor one parabolic region over two linear or three constant regions. If we have not reached the end of the 1D signal we continue the process by constructing a new K-level tree.

To demonstrate this algorithm consider the image in Fig.2 corrupted by additive Gaussian noise with σ=2 and 5% outliers.

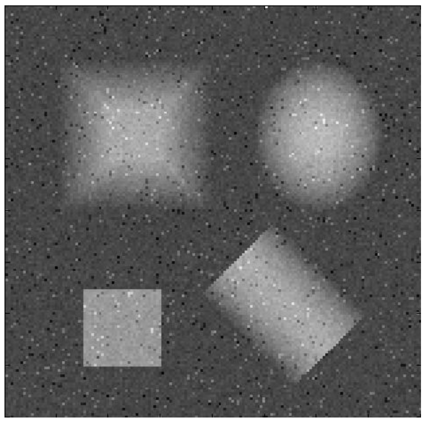

Fig. 2. Corrupted range image

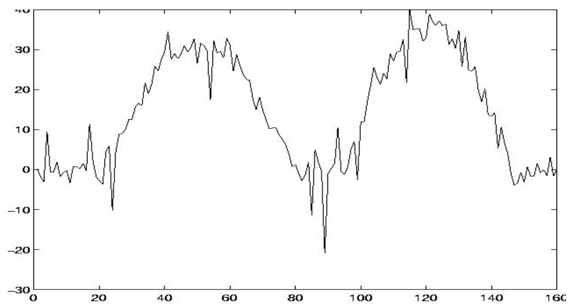

Fig. 3. The 50th row

The algorithm was applied to 50-th row of the image (Fig. 3). The obtained tree is shown in Fig. 4.

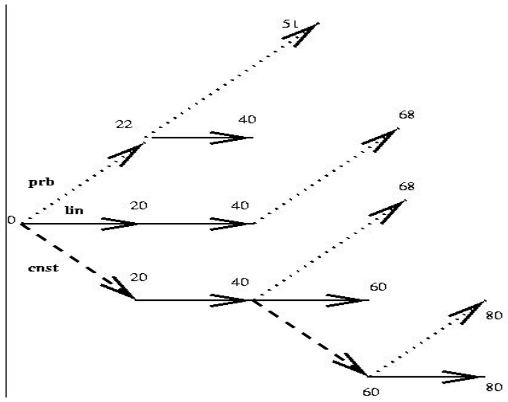

Fig.4. 4-level approximation tree

For this example the optimal path is const-lin-const-lin with C_{total} = (1+1.75+1+1.75)/80=0.07. Final optimal approximation is shown on Fig. 5.

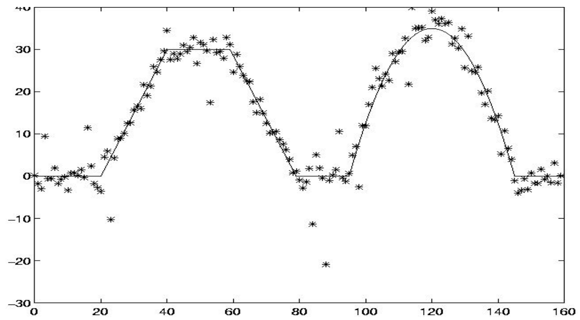

Fig.5. Optimal approximation of 50^{th} row

In many cases we have some prior information about the expected form of the signal. These constraints may be taken into account easily on the stage of the search for a minimal complexity path by considering only permitted ones.

3 Two-dimensional structure detection

The edge-points obtained in the previous stage do not necessarily lie on the boundaries. A heavy noise may result in the appearance of false edge-points and the disappearance or significant change in position of the real ones (overlapping effect). Using the region continuity we proceed with cleaning the set of labels that includes, in particular, overlapping analysis and elimination of solitary boundaries. Finally, each pixel is labeled as boundary, or as interior pixel with double label corresponding to vertical and horizontal approximation (e.g. the label CP denotes that the pixel belongs to constant region of row approximation and to parabolic regions of column approximation). On Fig. 6 we may see the edge map of the noisy image shown on Fig. 1.

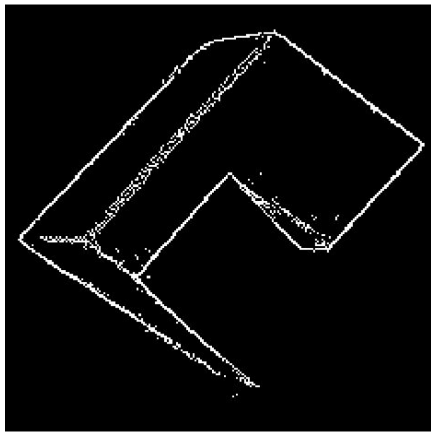

Fig. 6. Edge map

To detect a region it is sufficient to have information only about a group of pixels which almost certainly belong to the interior of a region. We call the union of such pixels *support region*. The process of obtaining support regions consists of expanding boundaries by adding all neighbors to them and thereby forming boundary layers. By deleting these layers and eliminating too small parts, we obtain the set of support regions.

Fig. 7. Support regions

For each support region its form is detected by analyzing the interior labels. For known form of the support region the parameters of the approximating surface are estimated by using the technique of Iteratively Reweighted Least Squares (IRSL) [5].

Knowing these parameters, we can restore the whole image or the interested us part of it (see Fig. 8.)

The experimental results illustrate the advantages of the proposed algorithm, which enables detection of the original structure of images, corrupted by heavy noise with outliers.

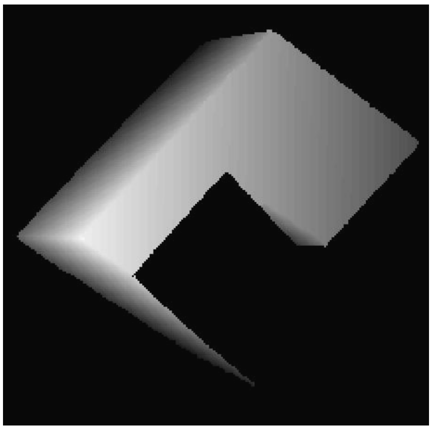

Fig. 8. Reconstructed image

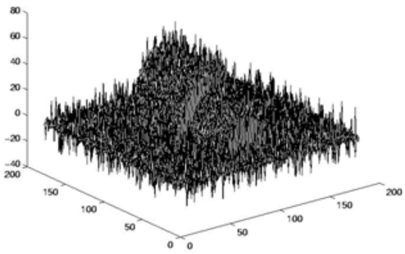

Fig. 9. Range image corrupted by Gaussian noise (σ=2.5) and 5% outliers

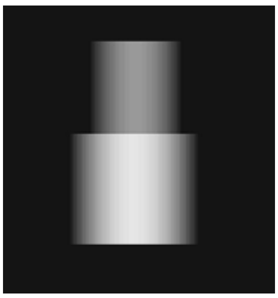

Fig. 10. Reconstructed image

4 Conclusion

The suggested approach has the following advantages:

- **Robustness** – detects and reconstructs range image surfaces contaminated by heavy composite noise.
- **Validity** – model selection procedure provides statistically justified image structure detection.
- **Efficiency** – the total running time is $O(N^{\frac{3}{2}})$, where N is a number of data points. The line-by-line analysis of the image is suitable for parallel computing that may reduce the running time to $O(N)$.
- **Adaptability** – multiresolution hypothesis testing permits the construction of problem-oriented algorithm by using of prior information.

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