A new multilevel line-based stereo vision algorithm based on fuzzy techniques

A. Luo

Mikroelektronik Anwendungszentrum
Hamburg GmbH
21079 Hamburg, Germany
luo@maz-hh.de

W. Tao and H. Burkhardt

Technische Informatik I
Technische Univ. Hamburg-Harburg
21079 Hamburg, Germany
{tao,burkhardt}@tu-harburg.d400.de

Abstract

This paper presents a multilevel algorithm for straight line extraction and matching from stereo intensity images based on fuzzy strategies. The ultimate goal of our work is to find 3D landmarks represented in the form of straight lines. In this method line extracting not only uses the information of current level but also considers the lines extracted at the coarser level. The idea is similar to multi-scale edge focusing, except that a fuzzy evaluation procedure is carried out to control the quality of a line candidate. This paper also proposes a new matching strategy based on fuzzy-sets, where various matching constraints can be effectively combined and some matching information from the coarser level is also considered. This method needs only one-step matching and avoids inadequate over-strong constraints, so that reliable unique line matches can be achieved with a relatively small cost.

1 Introduction

As a part of a vision system * for helping blind people to recognize some important landmarks appearing in their every-day lives, such as telephone booths, bus stops and so on [5], our task is to reconstruct the 3D structure of an object of interest. Since almost all of the important landmarks are artificial objects which usually can clearly be described by their 3D edges, the complete depth map of the object is not necessary. Some 3D properties are usually sufficient.

As it is known, the reconstruction of 3D structures from 2D images is an essential task for many visual problems. Stereo vision, as a fundamental technique for solving these problems, is intensively studied and various methods are widely developed. These methods are roughly classified in three main groups: intensity-based, area-based and feature-based methods [3]. Among them, the feature-based, or exactly, the line-based methods seem to be most interesting for our task. This is due to the fact that the shape of many 3D artificial objects is usually completely determined by their 2D and 3D straight lines. Besides, in most cases the straight lines can be obtained more easily and accurately from noisy images. Further more, straight lines possess more attributes than edge pixels or other primitive features and have sparse distribution [7].

Using straight lines as features for stereo matching needs reliable extraction of lines. In this paper we develop a multilevel algorithm for straight line extracting and matching based on fuzzy-sets. Compared with other existing methods, a great improvements for reliable feature extraction and matching can be achieved through a fuzzy guided coarse-to-fine tracking.

Without loss of generality, we apply the most popular stereo camera arrangement, i.e. lateral stereo model in this paper, where two stereo images are formed by the perspective projection of both binocular cameras with the focal length F and parallel optical axes separated by the baseline length B. In the lateral model, the matching is performed along horizontal epipolar lines, so that a simple epipolar constraint can be applied in line matching.

As mentioned above, the line extracting and matching algorithm is based on multilevel resolution. Fig. 1 illustrates only one level of the implementation. Beside the normal properties of 2D lines, e.g. geometric and grey parameters, we compute a fuzzy measurement representing the reliability or goodness of extracted lines and use it in each step: linking, merging, focusing and matching. A fuzzy measurement of line matching is also achieved according to fuzzy matching rules and used for the verification, recognition and at the finer level. After line matching, it is easy to compute the depth of the resulting object edges from disparities of matched lines.

2 Line extraction

Several well-known edge detectors, such as Roberts's,Prewitt's and Kirsch's operators, Marr and

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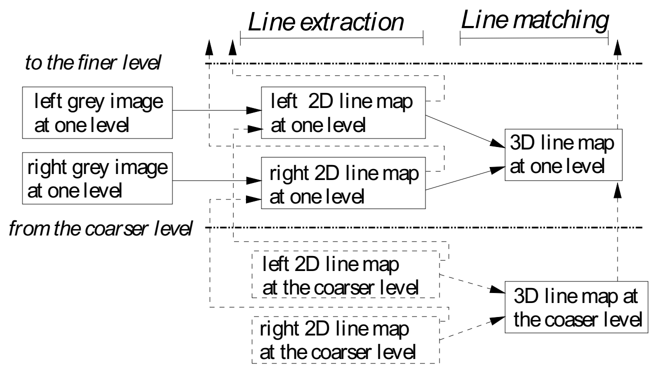

Figure 1: The block diagram of multilevel line-based stereo algorithm: only one level is shown here.

Hildreth's zero-crossing of Laplacian Gaussian, Haralick's zero-crossing of second directional derivatives and Canny's optimal edge detector, were proposed in the past years. In order to use grey attributes of straight lines for line matching, the gradient-based edge detectors are preferred. From the edge image one can extract straight lines further.

Line extraction is a high level process which groups primary edge pixels into line structures. Hough techniques can directly extract straight lines, but the information about the end points of a line segment and it grey attribute is not provided. Hence they are not very suited for line-based stereo. For this goal, Burns's method [2] seems to be more attractive. This method firstly segments neighboring pixels with similar gradient directions into line support regions and then directly extracts straight lines by fitting planes, where step-like edges are assumed. When applying it to a real image it is difficult to get the reliable complete line support regions. Another drawback of this method is the relatively high complexity. A primary method is also often used in line-based stereo, where edge pixels are linked and fitted into straight lines after edge detection and thinning. In order to improve the reliability and to reduce the fragmentation and complexity of these algorithms, the strategy of Scan-Label-Link-Merging is proposed in [9]. To avoid the noise and unnecessary details and to achieve a high positional accuracy, the hierarchical edge refinement (edge focusing) is proposed in [1]. The drawback of this method is the hard coarse-to-fine tracking, where unreliable coarse features are retained and new reliable features not appearing at the coarser level are not considered at the finer level.

For improving the above described methods, we propose a multilevel method of line extraction based on a fuzzy strategy. It has some advantages over [1]. Being different from [1], in this algorithm the coarse features are used to guide the whole process of Scan-Label-Link-Merging, which depends on the reliability of features and is determined by a fuzzy goodness measurement. New reliable features that do not come from the coarser level can be produced with fuzzy rules used in linking and merging. The multilevel implementation of the algorithm is shown in Fig. 1. The line extraction at each level has the following steps. (The details about them are described in [5].)

- Sobel's operator is used to compute the gradient images.
- edge pixels are selected in the gradient directions with the method of non-maximum suppression.
- edge pixels are grouped into segments, where the original scan-labeling method is improved with robust searching and thresholding for less fragments in all directions.
- line segments are obtained with fuzzy linking rules and guided by the reliable coarse straight line features. Line segments are evaluated with the fuzzy goodness measurement according to their grey identity, gradient magnitude, geometric error, fragmentation and/or reliability of the coarse predecessors.
- complete straight lines are obtained with fuzzy merging rules and guided by the reliable coarse straight line features. Lines are merged also according to the fuzzy goodness measurement which depends on their grey identity, gradient magnitude, geometric error, fragmentation and/or reliability of the coarse predecessors.

Due to the coarse guidance and robust linking and merging, so complete straight lines with less fragments can be extracted as reliably as possible. This eases consecutive steps such as line matching and object recognition. Unreliable coarse predecessors are not enforced to be retained always. The relative high positional accuracy of straight lines that leads also to satisfactory 3D estimation can be achieved at the correspondence level. These straight lines are used at the next finer level if necessary.

3 Line matching

In order to estimate 3D edges of objects from stereo images, it is necessary to build the correct correspondences of 2D edges on images by a matching process. Grey and geometric constraints and a-priori 3D modeling, e.g. similarity of features, epipolar constraints from stereo triangulation and various constraints of continuity are used in all stereo methods to reduce the searching space of correspondences, so that multiple matches can be disambiguated. Under relative high computational complexity, the most existing line based stereo algorithms use the paradigm of relaxation or dynamic programming to get one-to-one correspondences, where a set of reliable matches must often be achieved to initialize the whole matching process [7] [4]. One-step line matching was proposed in [6], where a match function evaluates the goodness of matching with many constraints. Practically, it is difficult to properly combine these constraints and weight them in the match function which affects the reliability of matching. For all existing line-based methods of stereo matching carefully selected and more explicit matching rules are required to eliminate false matches.

For reducing the complexity and achieving reliable line matches, we put forward a new multilevel algorithm combined with fuzzy techniques. The process of line matching is performed in one-step. Various matching constraints are treated by fuzzy evaluation functions, their relationship in the matching process are easily simplified by a set of fuzzy rules. The search space of matches are greatly reduced by coarse results, so that the multiple matches are easily eliminated. The unreliable or even wrong effects from the coarser level can be efficiently controlled by fuzzy evaluation and tracking. According to fuzzy matching goodness measurements, one can choose the reliable and one-to-one matches easily and weight their effects more efficiently on the same and the finer levels.

The corresponding multilevel implementation of line matching is shown in Fig. 1. The algorithm at each level is described as follows:

Line Matching: for the remaining strongest line L_i^l on the left image (until no proper lines exist)

- do all possible matching with the lines L_k^r (k=...) in a local window of the right image: $m_M(match(L_i^l, L_k^r))$ (see section 3.1 and 3.2)
- find the most reliable matching: $m_M(match(L_i^l, L_j^r)) = max(m_M(match(L_i^l, L_k^r)))$
- delete the line L_i^l on the left image. If $m_M(match(L_i^l, L_j^r))$ is larger than a fuzzy threshold, then establish a 3D edge and delete the line L_j^r on the right image too.

Improvement of 3D edges: linking fragmented 3D edges and incomplete structures.

- if a pair of neighboring 3D edges appear along a 3D line, then link both 3D edges and compute a new fuzzy evaluation based on goodness of its predecessors and the approximation.
- if both endpoints of an unmatched line are neighbored to a few of 3D edges on the 2D image space, then get the depth of this line and its fuzzy evaluation based on related 3D edges and their distances.

The fragments of 3D lines are satisfactorily eliminated in two steps, i.e. 2D line extraction and line matching.

3.1 Fuzzy matching rules

As it is usually done, our line matching algorithm uses the epipolar constraint, continuity constraint, constraint of grey and geometric similarities of lines for reducing the search complexity. By combing them into the following fuzzy matching rules, these constraints can be more efficiently treated.

IF line L_i^l on the left image and line L_k^r on the right image

1. overlap well in the vertical direction: $m_1(l_i^l, l_k^r)$ (epipolar constraint),
2. have the same angle: $m_2(\theta_i^l, \theta_k^r)$ (constraint of geometric similarity),
3. have the same gradient magnitude with identical sign: $m_3(g_i^l, g_k^r)$ (constraint of grey similarity),
4. have a similar disparity to some reliably matched adjacent strong 3D edges: $m_4(d)$ (continuity constraint),
5. have a similar disparity to the neighboring 3D edges estimated from the coarser level: $m_5(d)$ (multilevel transfer),

THEN L_i^l and L_k^r is a match,

where l is the vertical projection of L, θ is the angle of L, g is the gradient magnitude of L and d is the disparity of two lines L_i^l and L_k^r.

The above fuzzy rules can be described in a mathematical expression.

Definition of fuzzy evaluation function of line matching

$$m_M(match(L_i^l, L_k^r)) = min(m_1, m_2, m_3, m_4)\ m_5 \quad (1)$$

3.2 Fuzzy matching evaluation

To perform the above described matching process, we now define some fuzzy evaluation functions related to the fuzzy matching rules.

With the abbreviation function

$$S_w(x) = \begin{cases} 1 & : \ |x| \le w \\ 2 - (|x|/w) & : \ w < |x| < 2w \\ 0 & : \ 2w \le |x| \end{cases}$$

we define the following fuzzy evaluation functions as example:

$$\begin{aligned} m_1(l_i^l, l_k^r) &= S_{\Delta l}(log(l_i^l/l_k^r))\frac{overlap(l_i^l/l_k^r)}{min(l_i^l, l_k^r)} && (2) \\ m_2(\theta_i^l, \theta_k^r) &= S_{\Delta\theta}(\theta_i^l - \theta_k^r) && (3) \\ m_3(g_i^l, g_k^r) &= S_{\Delta g}(log(g_i^l/g_k^r)) && (4) \\ m_4(d) &= \frac{(k_0 + \sum_j k_j m_M(d_j) S_{\Delta d}(d - d_j))}{(k_0 + \sum_j k_j m_M(d_j))} && (5) \\ m_5(d) &= \frac{(k_0 + \sum_i k_i m_M(d_i) S_{\Delta d}(d - d_i))}{(k_0 + \sum_i k_i m_M(d_i))} && (6) \end{aligned}$$

where coefficient i in Eq. 6 is the number of the set of the neighboring 3D edges estimated from the coarser level, j in Eq. 5 is the number of the set of some selected neighboring and reliably matched 3D edges at this level, which however can also be empty. d_i and d_j are the disparities of a neighboring 3D edge estimated from the coarser level and at the same level separately with reliability $m_M(d_i)$ and $m_M(d_j)$. The weight coefficient k_i (or k_j) depends on the distance of the current line to match d and an existing neighboring line d_i:

$$k_i = S_{x_{max}}(|x(d) - x(d_i)| + x_{max}) \frac{overlap(l(d), l(d_i))}{min(l(d), l(d_i))}$$

with the maximal distance of correlation x_{max} and the horizontal coordinate x.

The epipolar constraint can not strictly be followed in Eq. 2 due to the fragmentation and imperfection in the line extraction. The constraint of continuity need not be strictly enforced and has only a loose effect in the fuzzy functions 5 and 6.

4 Experimental results

From the above discussion can see several advantages of our algorithm: 1. efficient line extraction, 2. robust line matching with reliable performance, and 3. low computational cost. To show the performances of this algorithm, two examples estimating 3D structures from the outdoor scenes are given in the following.

All scenes consist of a telephone booth and other man-made objects†. The extracted 2D straight lines and the matched 3D edges at various levels are shown separately in Fig. 2 and 3. In Fig. 2 the 3D structure of the telephone booth is detected reliably at the middle level, whereas in Fig. 3 the 3D edges of the telephone booth is already estimated satisfactorily at the coarsest level. In these examples, unnecessary details of the scenes are eliminated well and the complete structure of objects of interest is detected reliably. With the increase of resolution, the estimation of 3D edges is improved greatly. In summary, the 3D edges for all examples are well estimated. The accuracy is not discussed further due to space limit.

5 Conclusion

In this paper we discuss some problems about the existing methods of straight line extraction and matching. In order to improve these methods, new multilevel algorithms using fuzzy evaluation and guidance are put forward. The main difficulties, e.g. dilemma between completeness and fragmentation, accuracy and unnecessary details of line extraction etc. are satisfactorily solved by our new paradigm, where both the transfer of coarse features and the extraction of reliable features are selected with fuzzy evaluation and an edge focusing is optimally controlled by fuzzy guidance. The whole process of line matching is performed in one step, where unreliable results are avoided by fuzzy evaluation. Various matching constraints and their relationship in the matching process are therefore also easily simplified with the new fuzzy matching rules. By reducing the search space of matches with fuzzy tracking of coarse results, the multiple matches are easily eliminated, so that the optimal one-to-one line matching can be achieved under a low computational cost. As an extension of this work, we can expect to apply these methods to trinocular line-based stereo vision for improving the estimation accuracy of 3D straight edges. Besides, one can integrate the line-based stereo method with other stereo methods, e.g. intensity-based methods [3] for getting a dense depth map of scenes with reliable depth edges.

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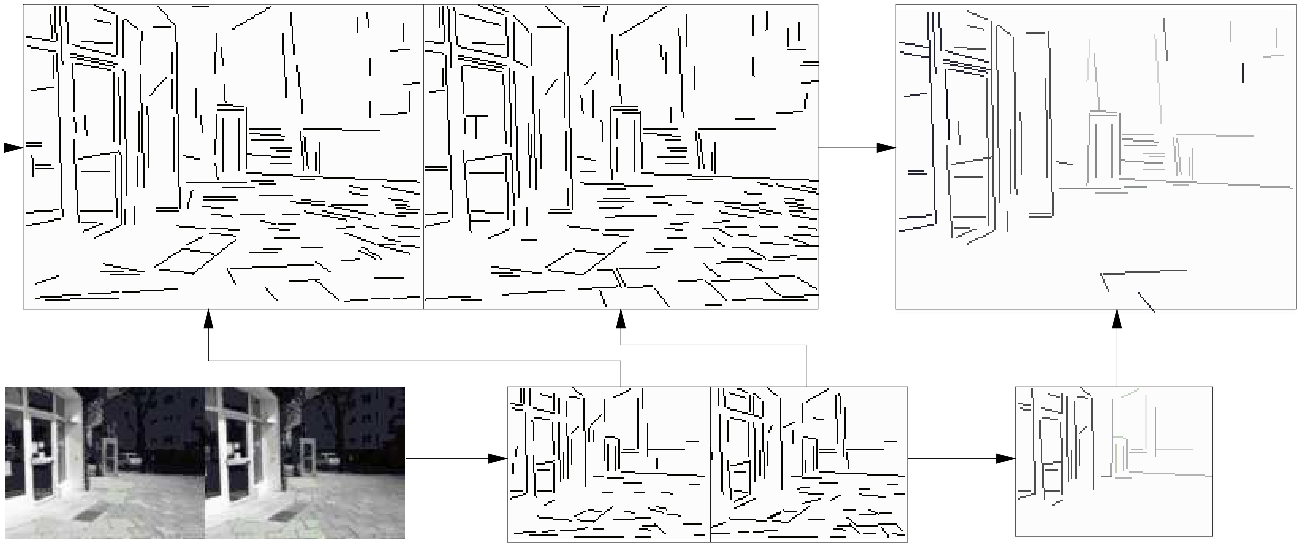

Figure 2: The telephone booth is approximately 15m away from the cameras and the 3D edges of all levels are shown at the right side.

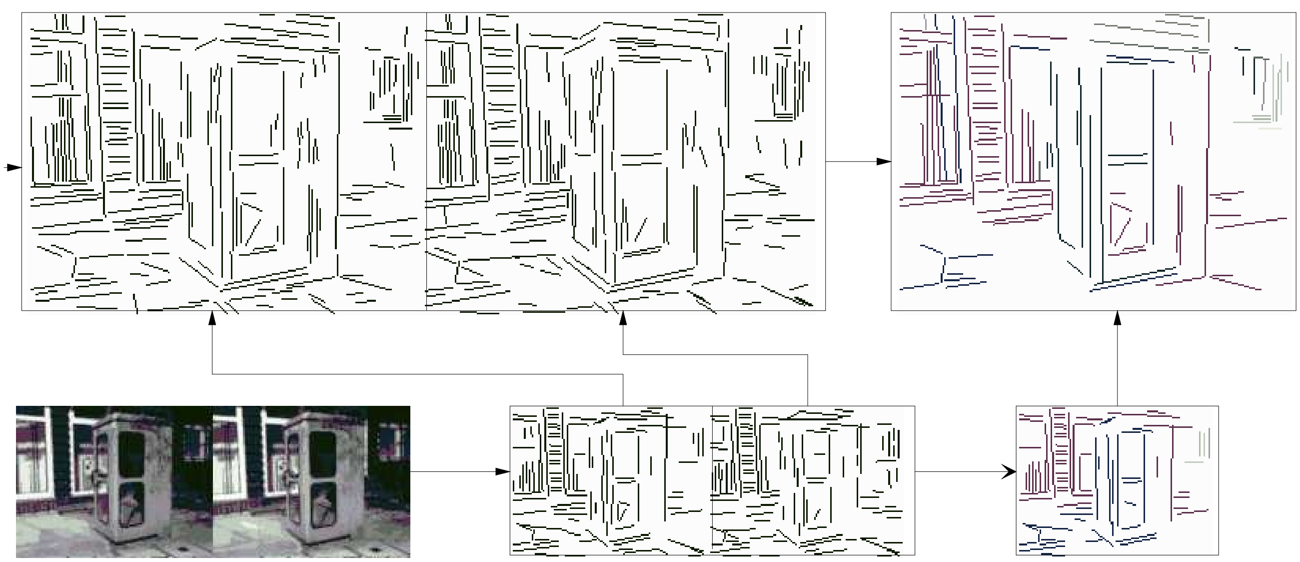

Figure 3: The telephone booth is approximately 5m away from the cameras and the 3D edges of all levels are shown at the right side. (the images and results of the finest level are not shown.)