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AUTOMATIC EXTRACTION OF LINEAR FEATURES USING MORPHOLOGICAL OPERATIONS AND MARKOV RANDOMFIELDS

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In this paper we have presented a model-based approach to the automatic extraction of linear features, in the images. This method consists of two steps. The first step utilizes local information related to the geometry and radiometry of the structures to be extracted. It consists of a series of morphological filtering stages. The resulting image serves as input to a line-following algorithm, which produces a set of line segments. In the second step, a segment linking process is carried out incorporating contextual, a priori knowledge about the object shape, with the use of Markov random field (MRF) theory. In this approach the extracted line segments, produced by the morphological operators, are organized as a graph. The linking process of these segments is then achieved through assigning labels to the nodes of the graph using domain knowledge of extracted line segments measurements and spatial relationships between the various line segments. The interpretation labels are modeled as a MRF on the corresponding graph and the linear feature identification. This type of problem is formulated as MAP (maximum a posteriori) estimation rule.

***Keywords**:* Linear features, MAP, MRF, Gradient and Random Field.

1. Introduction

Several approaches for linear feature extraction have been proposed in the literature, most of them dealing with the problem of linear feature identification by using either synthetic aperture radar (SAR) images or optic (visible range) images. In this method, we combined mathematical morphology and MRF technique for linear feature identifications in Images. It is a model-based approach that combines both local and global criteria about the geometry and radiometry of the linear structures of interest. The use of MRF theory succeeds in extending the results of the morphological filtering towards a better extraction of linear features.

2. Local Analysis

The features we search for linear featured objects are characterized by their geometry and image appearance. The linear featured objects like roads appear on an optical airborne image as thin, elongated structures with a maximum width w_{max}. They are locally rectilinear, with each object pixel belonging to a line segment that is longer than a minimum length l_0 and each object segment is considered as a bright structure with respect to its surrounding. All this information can be integrated and extracted using mathematical morphology. A series of morphological operators, adapted to the geometrical characteristics of the objects we want to identify, are successively applied to the input image. A line-following algorithm is then applied to the resulting image in order to produce a set of line segments.

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Step 1: We want to remove dark structures from the image, without influencing the shape of the bright elongated structures of interest. For this reason, we apply a morphological closing by reconstruction, using a square flat structuring element (SE) of size equal to $w_{max}/4$.

Step 2: Linear featured object segments correspond to elongated bright regions with a certain width. In order to eliminate bright structures that do not belong to any line segment with minimum length l_0, we apply on the reconstructed image of step 1 a morphological opening by using l_0 pixels long linear structuring elements successively oriented in 32 possible directions. The resulting value at each pixel is the supremum of all these directional openings.

Step 3: In this step, we eliminate very wide linear bright structures that correspond to objects larger than the specified objects. Initially, we perform a morphological closing operation with a square SE of size $w_{max}/4$, in order to remove remaining dark spots from the image. After this, we retain only bright structures with widths less than w_{max}, by applying an opening top-hat operator with a flat square SE of size w_{max}. The remaining structures correspond to the roads that we want to extract. Finally, we apply once again closing with a flat square SE of size $w_{max}/4$, in order to make the regions inside the roads more uniform.

Step 4: The final result of step 3 gives a higher response at the points belonging to the roads compared with the surrounding background. An easy way to extract the road regions would be the application of a threshold to the resulting image as in [1]. Unfortunately, this leads to partial detection of the roads disconnected segments, together with some spurious results corresponding to false alarms. In order to overcome this problem, and to produce one pixel width line segments, we extract, from the resulting image of step 3, the pseudo-medial axis of the objects, over which we apply a line-following algorithm using the orientation of the SE which produces the supremum of the directional openings. The pseudo-medial axis of the objects is extracted by performing the watershed transformation on the response image .

3. GLOBAL ANALYSIS

The global analysis step of our approach is based on the earlier work of Tupin *et al.* [10] and is carried out on the level of the road segments. A graph is built, which contains all possible connected line segments that are created by using some connectivity criteria. The object identification process is then treated as an optimum graph labeling problem. This is carried out by associating an energy function to the line segments, based on a Markovian model of linear featured objects. Given the observation process, the minimization of this energy function will produce the best configuration of the line segments.

Step 1: Graph Creation

We will denote by S_{det} the set of the detected line segments. Each segment of S_{det} is defined by its endpoints. Two line segments of S_{det} can be connected if their distance is less than a fixed threshold, and if the angle between them is less than a specified value. We create a new set S_{con}, which corresponds to all possible connections between the elements of S_{det}. Let $S = \{S_{det}, S_{con}\}$, with its cardinality denoted by N.

For each line segment $i \in S$ we assign a saliency measure R_i defined as:

$$R_I = I / (|\theta - \acute{\alpha}| + 1) \quad (1)$$

where I is the mean value of the morphological object detection response, along the line segment is the line segment orientation, and $\acute{\alpha}$ is the mean value of the morphological object detection orientation response, along the line segment. We associate a graph structure (G) to the set S, each segment i belonging either to S_{det} or S_{con} being one of its nodes, and two nodes i and j being linked by an arc if they share a common endpoint. In order to introduce contextual knowledge with the use of a Markovian model, we must define a neighbourhood system. The neighbourhood N_i of each node i contains all the line segments that have a common endpoint with i. For each segment $i \in S_{det}$ we define cliques that correspond to both of its end points. Each of these cliques contains all the segments that share the specific extremity. If N_{det} denotes the number of elements of S_{det}, then the total number of cliques equals 2 xN_{det}.

After the definition of our neighborhood system, we attach attributes to the nodes and arcs of G. The arc between nodes i and j is associated with a value θ_{ij} representing the angle between the two segments. For each node $i \in S$, we associate a normalized length l_i and an observation value d_i that reflects the probability of this segment belonging to the object. d_i should increase when, adjacent to it, segments belong also to the object, something that rises from the continuity that characterizes our region of interest. For this reason we express d_i as a function of the saliency measures r_k:

$$d_i = \max_{j \in NI} \{(ri + rj)/2\} \quad (1)$$

The identification of the object will be carried out with an appropriate labeling of the graph. A label l_i is associated to each node i with $l_i = 1$ if i is a part of the object and $l_i = 0$ otherwise. The optimum configuration $L = (l_1, l_2, \ldots; l_N)$ of the segments of S, given the observation process $D = (d_1, d_2, \ldots, d_N)$, can be estimated with a MAP criterion that maximizes the posterior probability distribution given by:

$$P(l \mid d) = p(d|l)\, P(l)/p(d) \quad (2)$$

where $P(l)$ is the prior probability of labelings l, $p(d/l)$ is the conditional probability distribution function (p.d.f.) of the observations d, also called the likelihood function of l for d fixed, and $p(d)$ is the density of d which is a constant when d is given.

Step 2: Energy Definition

We consider that the conditional probability distribution $p(d/l)$ corresponds to a Gibbs distribution. By assuming independence between the different observations (d_i) and supposing that the conditional probability distribution of d_i only depends on the labelings l_i, we can write

$$p(d|\,1) = \Pi_{i=1}^{N} p(d_i/l_i) \;\alpha\; \exp(-5\Sigma_{i=1}^{N} V(d_i/l_i)) \quad (3)$$

where $V(d_i/l_i)$ denotes the potential of segment i. This type of potential can be deduced from the observation field D and reflects the likelihood of every segment as belonging or not to a road.

The conditional probability distributions $p(d_i/l_i)$ are learned from an experiment after a manual segmentation of the objects, performed by a human observer. After this experiment, we notice that object segments may have almost any observation value d, while non-linear segments have observations with values greater than a threshold t. Based on this heuristic; the following linear conditional potentials have been chosen:

$$V(d \mid 0) = \begin{cases} \dfrac{d}{t} & \text{if } d < t \\ 1 & \text{otherwise} \end{cases} \quad \text{and } V(d \mid 1) = 0, \forall d$$

In order for the potentials to correspond to a probability distribution, we normalize the values $V(d|l)$ so that:

$$\int_0^1 p(d = x|1)dx = \int_0^1 \exp[-V(d = x|1)]dx = 1$$

This condition holds for the potentials that correspond to object segments, as they are equal to zero. For the non-linear object segments, potentials of the form:

$V(d_i/0) + \log Z_0$ are used; Z_0 denotes a normalization factor given by:

$$Z_0 = (1 - t)(1/e) - t(1/e - 1), \text{with } e = \exp(1).$$

Step 3: Prior Probability of Labeling

The previous models are based on the assumptions that objects like roads are long structures with low curvature and that intersections between them are rare. By considering the label field L as a MRF, we can use once again the MRF-Gibbs field equivalence in order to introduce a priori knowledge to the object identification task. The prior probability of labelings $P(l)$ can be expressed in terms of an energy function $U(l)$ as:

$$P(L = l) = 1/Z_1 \exp(-U(l)) \qquad (4)$$

where Z_1 is the partition function and $U(l) = \sum_{c\in C} V_c(l)$. The clique potentials $V_c(l)$ carry a priori information about the geometrical characteristics of the features to be extracted. Every clique c contains one segment belonging to S_{det}(with length l^{det}), along with the segments of S_{con} (with length l_{con}) that share the same extremity. Based on the main assumptions of our object model, we have chosen the following potentials for every clique c:

$$\forall i \in c, li = 0 \Rightarrow Vc(l) = 0 = 0 \qquad (5)$$

$$\exists! i \in {}^c/li = 1 \Rightarrow V_c(l) = K1 + 1 - l_i^{det} + \log Zo \qquad (6)$$

$$\exists!(i, j) \bullet c^2 D \; li = lj = 1$$

$$\Rightarrow \quad Vc(l) = \sin(\theta\, ij) + 1 - l_i^{det} + l_j^{con} + 2\log Zo \qquad (7)$$

in all other cases,

$$V_c(l) = K_2 \sum_{i/i\in c} li \qquad (8)$$

Equation 5 describes a null situation, which does not have to be penalized or favored with respect to the a priori assumptions about the object structure. In equation 6, by choosing $K_1 > 0$ we penalize short objects: i.e. the clique potential is high for a clique with only one isolated segment, except when this isolated segment has a high normalized length l_i^{det} (close to 1). High values of K_1 favor more connected configurations. Equation 7 imposes the constraint of low curvature and at the same time penalizes configurations with short detected and long connecting segments. Finally, $K_2 > 0$, in equation 8, makes less probable the appearance of crossroads.

The additional factors $\log Z_0$ and $2\log Z_0$, in equations 6 and 7 respectively, facilitate the comparison between the clique potential values and the conditional potentials of the null configurations (where all the segments of the current clique are labeled as 0). In the case of a clique with one segment labeled as 1, the factor $K_1 + 1 - l_i^{det}$ in equation 6 is directly compared with the conditional potential component $V(d_i/0)$ of the current segment i. In the case of a Clique with two segments i, j labeled as 1, the factor $\sin(\theta_{ij}) + 1 - l_i^{det} + l_j^{con}$ of equation 7 is compared with the sum of the conditional potential components $V(d_i \mid 0)$, $V(d_j \mid 0)$.

Step 4: Posterior Probability

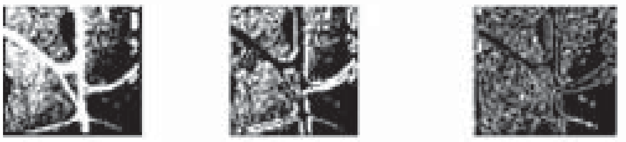
The posterior probability $P(l/d)$ can be also expressed in terms of a global energy function $U(l|d)$, which can be deduced from the potentials described in the previous steps:

$$P(l|d) = z^{\frac{1}{2}} \exp(-U(l \mid d)), U(l \mid d) = \sum_{i=1}^{N} V(di|li) + \sum_{c\in C} Vc(l) \qquad (9)$$

The MAP configuration of the line segments can be estimated by minimizing the energy function $U(l|d)$.

4. RESULTS

Original BMP. After morphological operations. After MRF Model



Original BMP After Morphological operations. After MRF Model

Road BMP After Morphological Operations. After MRF Model

5. DISCUSSION AND CONCLUSIONS

The model-based technique for linear feature extraction, in digitized images, which combines both local and global criteria; its main advantage is the high detection performance in heavily textured environments along with its ability of identifying elongated structures independently of their size. Concerning the local analysis step, we utilized the morphological operators proposed by Chanussot *et al.*[1], in order to identify linear structures with specific geometrical properties. Additionally, we extracted the linear feature main axis and applied a line-following algorithm. This process produced a set of line segments with meaningful orientation properties and eliminated a sufficient number of false alarms.

In the next step of our work, we created a Markovian linear model; similar to the one proposed by Tupin *et al* [6.] in order to introduce contextual knowledge to our analysis. At the same time, we proposed some necessary modifications in order to incorporate additional information about the nature of the line segment candidates. These include a discrimination between the initially detected segments (S_{det}) and the ones corresponding to the possible connections (S_{con}), the introduction of a new observation measure (d_i) that reflects more efficiently the likelihood value of each segment and the use of fewer number of potential parameters (t, K_1, K_2). One of the most important limitations of our method is that it is not entirely unsupervised, due to the setting of five parameters, two of them concerning the local analysis step (w_{max}, l_0) and three (t, K_1, K_2) influencing the linking process. The parameters w_{max}, l_0 are based on a priori knowledge about the size of the object. On the other hand, the proposed ranges of the parameters t, K_1, K_2, give optimal results for this type of environments, independently of the size of the linear features of interest. Further analysis should be carried out towards the problem of identifying segments with high curvature, especially when this is higher that the maximum object width found in the image and in the choice of a more efficient skeletonization process for the extraction of the object main axis. Finally, improvements could be obtained during the connection step, by searching for the best path between extremities of the segments we want to connect, instead of assuming that all objects may be found by connecting a set of initially detected segments. Even the modified version of this method could not produced accurate result for noise Images.

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