

Randomized Hough Transform

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INTRODUCTION

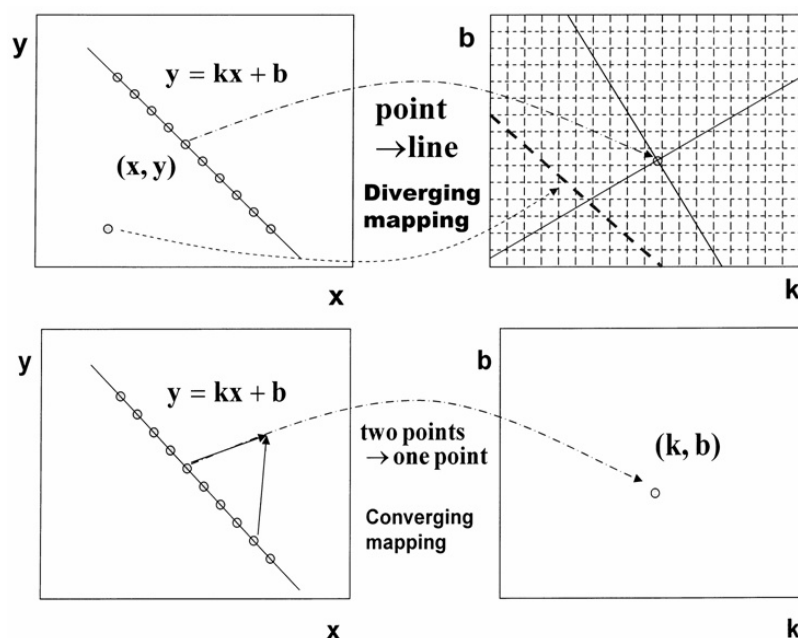
Proposed in 1962, the Hough transform (HT) has been widely applied and investigated for detecting curves, shapes, and motions in the fields of image processing and computer vision. However, the HT has several shortcomings, including high computational cost, low detection accuracy, vulnerability to noise, and possibility of missing objects. Many efforts target at solving some of the problems for decades, while the key idea remains more or less the same. Proposed in 1989 and further developed thereafter, the Randomized Hough Transform (RHT) manages to considerably overcome these shortcomings via innovations on the fundamental mechanisms, with random sampling in place of pixel scanning, converging mapping in place

of diverging mapping, and dynamic storage in place of accumulation array. This article will provide an overview on advances and applications of RHT in the past one and half decades.

BACKGROUND

Taking straight line detection as an example, the upper part of Fig. 1 shows the key idea of the Hough Transform (HT) (Hough, 1962). A set of points on a line $y=kx+b$ in the image are mapped into a set of lines across a point (k, b) in the parameter space. A uniform grid is located on a window in the (k, b) space, with an accumulator $a(k, b)$ at each bin. As each point (x, y) on the image is mapped into a line in the (k, b) space, every associated accumulator $a(k, b)$ is incremented by 1. We can detect

Figure 1. From hough transform to randomized hough transform



lines by finding every accumulator with its score $a(k, b)$ larger than a given threshold.

The Hough Transform was brought to the attention of the mainstream image processing community by Rosenfeld (1969). Then Duda and Hart (1972) not only introduced the polar parameterization technique for more efficient line detection, but also demonstrated how a circle can be detected. Kimme, Ballard and Sklansky (1975) made circular curve detection significantly more effective by using the gradient information of pixels. Merlin and Faber (1975) showed how the HT could be generalized to detect an arbitrary shape at a given orientation and a given scale. Ballard (1981) eventually generalized the HT to detect curves of a given arbitrary shape for any orientation and any scale. Since then, a lot of applications, variants and extensions of the HT have been published in the literature. A survey on these developments of the HT is given by Illingworth and Kittler (1988).

However, the HT has several critical drawbacks as follows:

- a. All pixels are mapped, and every bin in the grid needs an accumulator. If there are d parameters, each represented by M bins or grid points, one needs M^d accumulators.
- b. To reduce the computational cost, quantization resolution cannot be high, which blurs the peaks and leads to low detection accuracy.
- c. Each pixel activates every accumulator located on a line, but there is only one that represents the correct one while all the others are disturbances.
- d. If the grid window is set inappropriately, some objects may locate outside the window and thus cannot be detected.
- e. Disturbing and noisy pixels cause many interfering accumulations.

Many efforts have been made to alleviate these problems. Using the gradient information of pixels is one of them. Another is analyzing noise and error sensitivity (van Veen, 1981; Brown, 1983; Grimson & Huttenlocher, 1990). The third is the use of hierarchical voting accumulation (Li, Lavin & LeMaster, 1986) or multiresolution (Atiquzzaman, 1992). Yet another is improving the effect of quantization through the use of kernels (Palmer, Petrou, & Kittler, 1993) or error propagation analysis (Ji & Haralick, 2001), as well as hypothesis testing (Princen, Illingworth, & Kittler,

1994). However, none of these suggestions offer any fundamental changes to the key mechanisms of HT.

Proposed in 1989 and further investigated thereafter (Xu, Oja, & Kultanen, 1990; Xu & Oja, 1993), the Randomized Hough Transform (RHT) tackles the above problems by using a fundamental innovation: the one-to-many diverging mapping from the image space to the parameter (accumulator) space, as shown in the upper part of Fig. 1(a), is replaced by a many-to-one converging mapping, as shown in the bottom part of Fig. 1(a). This fundamental change further enables several joint improvements, such as a random sampling in place of pixel scanning, a small size dynamic storage in place of the array of M^d accumulators, and an adaptive detection in place of enumerating all the pixels and picking those accumulators with scores larger than a threshold. As a result, not only time and storage complexity have been reduced significantly, but also the detection accuracy has been improved considerably.

Subsequently, many studies have been made on RHT. On one hand, there are various real applications such as medical images (Behrens, Rohr, & Siegfried, 2003), range images (Ding, et al, 2005), motion detection (Heikkonen, 1995), object tracking for a mobile robot (Jean & Wu, 2004), soccer robot (Claudia, Rous, & Kraiss, 2004), mine detection (Milisavljevic, 1999), and others (Chutatape & Guo, 1999). On the other hand, there are also many further developments on RHT, including an efficient parameterization for ellipse detection (McLaughlin, 1998), extension to motion detections (Kalviainen, Oja, & Xu, 1991; Xu, 2007), the uses of local gradient information, local connectivity and neighbor-orientation for further improvements (Brailovsky, 1999; Kalviainen & Hirvonen, 1997), an integration with error propagation analysis (Ji & Xie, 2003), a modification of random sampling to importance sampling (Walsha & Raftery, 2002), and others (Xu, 2007). Due to space limit, it is not possible to provide a complete survey here. An early review on RHT variants is referred to (Kalviainen, Hirvonen, Xu, & Oja, 1995), and recent elaborations on RHT are referred to (Xu, 2007).

It may also need to be mentioned that the literature on RHT studies often includes studies under the name of probabilistic HT (Bergen & Shvaytser, 1991; Kiryati, Eldar & Bruckstein, 1991) that also suggests to use a random sampling to replace the scanning in the implementation of the standard HT and thus shares one

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