# Isotropic Granularity-tunable gradients partition (IGGP) descriptors for human detection

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This paper presents a new descriptor for human detection in still images. It is referred to as isotropic granularity-tunable gradients partition (IGGP), which is extended from granularity-tunable gradients partition (GGP) descriptors. The isotropic representation is achieved by aligning the features with different orientation channels according to their principal angles. The benefits of this extension are two folds: firstly, since the partitions' sizes of all the orientation channels are equal, the noise introduce by the small partitions in the original GGP descriptors is eliminated and the performance can be essentially improved; secondly, the integral image based fast computation is applied and more than 20 times speedup has been achieved. In addition, we introduce a new human dataset HIMA. Unlike the previous available human datasets which are mainly captured on the street views for automobile safety or robotics, HIMA dataset is captured on the outdoor work fields for industry safety. The major challenges include: extreme light conditions, occlusion and strong noise. We benchmark several promising detection systems, providing an overview of state-of-the-art performance on the HIMA set. Experimental results show that the proposed method can yield very competitive results in both the detection speed and accuracy.

Recently, remarkable progress has been achieved [1, 2, 4, 5] for human detection. Granularity-tunable gradients partition (GGP) descriptor was proposed by Liu et al. [3], in which granularity is used to define the spatial and angular uncertainty of the line segments in the Hough space. In the formulation of GGP, the feature extraction contains two steps: firstly, the image is parsed as the combination of the generalized lines by orientation space partition; secondly, the heterogeneous GGP feature vector is calculated within the generalized lines. By this means, the GGP descriptor can encode both the geometrical structure and the statistical summarization of the objects.

The rationale of GGP is reasonable but there are some difficulties in its implementation part. The partitions are uneven for the channels whose principal orientations are not equals to 90° or 0°. Since the size of the partitions are different, on the one hand, the center partitions with bigger size become dominant and the contributions of the other partitions are suppressed; on the other hand, the minor partitions can introduce noise because its insufficient gradient points makes the feature values become statistically unstable. Moreover, the shapes of the partitions are different, which makes the fast computation intractable.

The difficulties mentioned above motivate the works of this paper. By introducing the isotropic feature representation, a substantial performance improvement is observed and the computation complexity is reduced from $O(n*w*h)$ to $O(n)$, where $n$ is the number of orientation partition and $(w,h)$ is the size of the feature window. Practically, 23 times speedup is achieve by IGGP over GGP.

For a given image $I$, we divide it into $n$ orientation channels. Then each orientation channel $Q_{\theta_i}$ is rotated by angle $90° - \theta_i$. This rotated channel is referred to as $Q'_{\theta_i}$. The position $(x,y)$ in the $Q_{\theta_i}$ coordinate frame is mapped to $(x',y')$ in the $Q'_{\theta_i}$ coordinate frame, as in Figure.1.

We maintain six integral images for each channel. Since all the partitions in the feature window are the rectangles with upright positions, the heterogeneous features can be calculated by the integral image with constant number of computations. Here we just give an example on how to calculate the standard deviation of positions along the tangent direction of partition $r$ in Equ.1. The computation of other elements are straightforward.

$$v_{tang} = \sqrt{Y2_r/C_r - m_y^2}/h \tag{1}$$

All the values, $m_y$, $Y2_r$, $C_r$ and $Y_r$ can be calculated by integral images easily.

Given a feature window $R(x_c, y_c, w/2, h/2)$, the computation complexity of IGGP is $O(n)$, where $n$ is the number of orientation partition; the computation complexity of GGP is $O(n*w*h)$. In practical computation, a 23 times speed up can be achieved by IGGP over GGP.

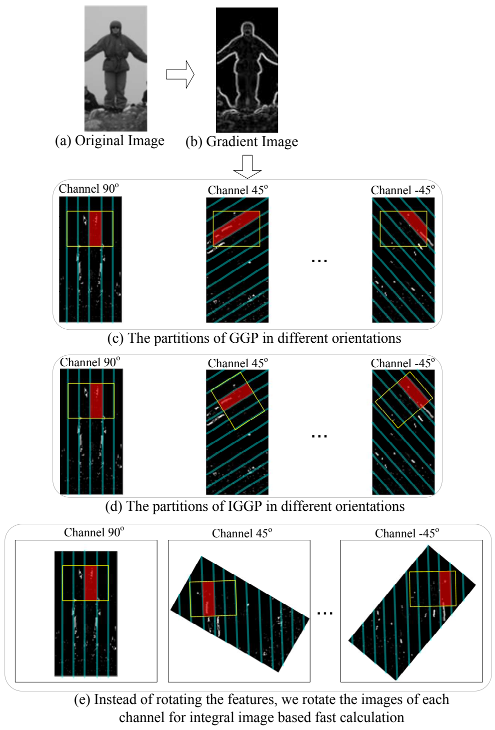


Figure 1: The difference between GGP and IGGP

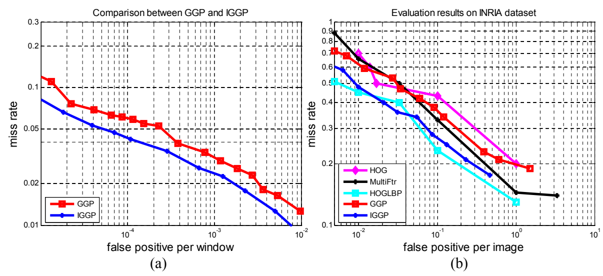


Figure 2: Evaluation results on INRIA dataset. (a) The comparison between GGP and IGGP base on FPPW criteria. (b) The comparison between IGGP and the state of the art methods base on FPPI criteria.

We evaluate the IGGP against GGP and the state of the are methods in Figure.2(a) and (b).

[1] Navneet Dalal and Bill Triggs. Histograms of oriented gradients for human detection. In *CVPR*, pages 886–893, 2005.

[2] Piotr Dollar, Boris Babenko, Serge Belongie, Pietro Perona, and Tu Zhuowen. Multiple component learning for object detection. In *ECCV*, pages 211–224, 2008.

[3] Yazhou Liu, Shiguang Shan, Wenchao Zhang, Wen Gao, and Xilin Chen. Granularity-tunable gradients partition (ggp) descriptors for human detection. In *CVPR*, pages 1255 – 1262, 2009.

[4] Xiaoyu Wang, Tony X. Han, and Shuicheng Yan. An hog-lbp human detector with partial occlusion handling. In *ICCV*, pages 32–39, 2009.

[5] Christian Wojek, Stefan Walk, and Bernt Schiele. Multi-cue onboard pedestrian detection. In *CVPR*, 2009.