SPEEDED UP IMAGE MATCHING USING SPLIT AND EXTENDED SIFT FEATURES

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Abstract: Matching feature points between images is one of the most fundamental issues in computer vision tasks. As the number of feature points increases, the feature matching rapidly becomes a bottleneck. In this paper, a novel method is presented to accelerate features matching by two modifications of the popular SIFT algorithm. The first modification is based on splitting the SIFT features into two types, Maxima- and Minima-SIFT features, and making comparisons only between the features of the same type, which reduces the matching time to 50% with respect to the original SIFT. In the second modification, the SIFT feature is extended by a new attribute which is an angle between two independent orientations. Based on this angle, SIFT features are divided into subsets and only the features with the difference of their angles less than a pre-set threshold value are compared. The performance of the proposed methods was tested on two groups of images, real-world stereo images and standard dataset images. The presented experimental results show that the feature matching step can be accelerated 18 times with respect to exhaustive search without losing a noticeable portion of correct matches.

1 INTRODUCTION

Matching a given image with one or many others is a key task in many computer vision applications such as object recognition, images stitching and 3D stereo reconstruction. These applications require often real-time performance. The matching is usually done by detecting and describing key-points in the images then applying a matching algorithm to search for correspondences.

Classic key-point detectors such as Difference of Gaussians (DoG) (Lowe, 2004), Difference of Means (DoM) (Bay et al., 2008) and Harris corner detector (Harris & Stephens, 1988) use simple attributes like blob-like shapes or corners.

For the key-point description a variety of key-point descriptors have been proposed such as the Scale Invariant Feature Transform (SIFT) (Lowe, 2004), Speeded Up Robust Features (SURF) (Bay et al., 2008) and Gradient Location and Orientation Histogram (GLOH) (Mikolajczyk & Schmid, 2005).

To robustly match the images, point-to-point correspondences are determined using similarity measure for Nearest Neighbour (NN) search such as Euclidean distance. After that, the RANdom Sample Consensus (RANSAC) method is applied to estimate the correct correspondences (inliers).

The combination of the DoG detector and SIFT descriptor proposed in (Lowe, 2004) is currently the most widely used in computer vision applications due to the fact that SIFT features are highly distinctive, and invariant to scale, rotation and illumination changes. In addition, SIFT features are relatively easy to extract and to match against a large database of local features. However, the main drawback of SIFT is that the computational complexity of the algorithm increases rapidly with the number of key-points, especially at the matching step due to the high dimensionality of the SIFT feature descriptor.

In order to overcome the main SIFT drawback, various modifications of the SIFT algorithm have been proposed. In general, the strategies dealing with the acceleration of SIFT features matching can be classified into three different categories: reducing the descriptor dimensionality, parallelization and exploiting the power of hardware (GPUs, FGPAs or multi-core systems) and Approximate Nearest Neighbor (ANN) searching methods.

(Ke & Sukthankar, 2004) applied Principal Components Analysis (PCA) to the SIFT descriptor. The PCA-SIFT reduces the SIFT feature descriptor

dimensionality from 128 to 36, so that the PCA-SIFT is fast for matching, but seems to be less distinctive than the original SIFT as demonstrated in a comparative study by (Mikolajczyk & Schmid, 2005).

(Bay et al., 2008) developed the Speeded Up Robust Feature (SURF) method that is a modification of the SIFT method aiming at better run time performance of features detection and matching. This is achieved by two major modifications. In the first one, the Difference of Gaussian (DoG) filter is replaced by the Difference of Means (DoM) filter. The use of the DoM filter speeds up the computation of features detection due to the exploiting integral images for a DoM implementation. The second modification is the reduction of the image feature vector length to half the size of the SIFT feature descriptor length, which enables quicker features matching. These modifications result in an increase computation speed by a factor 3 compared to the original SIFT method. However, this is insufficient for real-time requirements.

In recent years, several papers (Heymann et al., 2007) were published addressing the use of the parallelism of modern graphics hardware (GPU) to accelerate some parts of the SIFT algorithm, focused on features detection and description steps. In (Charriot & Keriven, 2008) GPU power was exploited to accelerate features matching. These GPU-SIFT approaches provide 10 to 20 times faster processing allowing real-time application.

The matching step can be speeded up by searching for the Approximate Nearest Neighbor (ANN) instead of the exact nearest neighbor. The most widely used algorithm for ANN is the kd-tree (Firedman et al., 1977), which successfully works in low dimensional search space, but performs poorly when feature dimensionality increases. (Lowe, 2004) used the Best-Bin-First (BBF) method, which is expanded from kd-tree by modification of the search ordering so that bins in feature space are searched in the order of their closest distance from the query feature and stopping search after checking the first 200 nearest-neighbor candidates. The BBF provides a speedup factor of 2 times faster than exhaustive search while losing about 5% of correct matches. In (Muja & Lowe., 2009) Muja and Lowe compared many different algorithms for approximate nearest neighbor search on datasets with a wide range of dimensionality and they found that two algorithms obtained the best performance, depending on the dataset and the desired precision. These algorithms used either the hierarchical k-means tree or multiple randomized kd-trees.

In this paper, a novel strategy which is distinctly different from all three of the above mentioned strategies, is introduced to accelerate the SIFT features matching step. The paper contribution is summarized in two points.

Firstly, in the key-point detection stage, the SIFT features are split into two types, Maxima and Minima, without extra computational cost and at the matching stage only features of the same type are compared. since correct match can not be expected between two features of different types.

Secondly, in the orientation assignment stage the SIFT feature is extended by a new attribute without extra computational cost. The novel attribute is an angle between the original SIFT feature orientation and a new different orientation ϕ. Hence SIFT features are divided into a few clusters based on the introduced angle. At the matching stage, only features of the almost same angle are compared. The idea behined this is that correct matches can be expected only between two features whose angles differ for less than a pre-defined threshold.

The proposed method can be generalized for all local feature-based matching algorithms which detect two or more types of key-points (e.g. DoG, LoG, DoM) and whose descriptors are rotation invariant, where two different orientations can be assigned (e.g. SIFT, SURF, GLOH).

2 ORIGINAL SIFT METHOD

The Scale Invariant Feature Transform (SIFT) method, proposed by Lowe (Lowe, 2004), takes an image and transforms it into a set of local features. The SIFT features are extracted through the following three stages:

1. Feature Detection and Localization: In this stage, the locations of potential interest points in the image are determined by detecting the extrema of Difference of Gaussian (DoG) scale space. For searching scale space extrema, each pixel in the DoG images is compared with its 26 neighbors in 3×3 regions of scale-space. If the pixel is lower/larger than all its neighbors, then it is labelled as a candidate key-point. Each of these key-points is exactly localized by fitting a 3D quadratic function computed using a second order Taylor expansion around key-point location. Hence key-points are filtered by discarding points of low contrast and points that correspond to edges.

2. Feature Orientation Assignment: An orientation is assigned to each key-point based on local image gradient data. For each pixel in a certain region R

around the key-point location, the first order gradients are calculated according to the following equations:

$$g_x = L(x+1, y, \sigma) - L(x-1, y, \sigma)$$
$$g_y = L(x, y+1, \sigma) - L(x, y-1, \sigma) \qquad (1)$$

where $L(x, y, \sigma)$ is the grey value of the pixel $p(x, y)$ in the image blurred by a Gaussian Kernel whose size is determined by σ.

The gradient magnitude and orientation for each pixel are computed respectively as follows:

$$m(x, y) = \sqrt{(g_x)^2 + (g_y)^2}$$
$$\theta(x, y) = \arctan(g_y / g_x) \qquad (2)$$

From gradient data (magnitudes and orientations) of pixels within the region R, a 36-bin orientation histogram is constructed covering the range of orientations [-180°, 180°] (each bin covers 10°). For each bin, the histogram is calculated according to following formulas:

$$ori(i) = \text{int}(\theta(x, y) / 10) - 17 \qquad (3)$$

where $\theta(x, y) \in [0°, 360°)$

$$mag(i) = \sum_R m_i(x, y) \Big/ \sum_R m(x, y) \qquad (4)$$

where $m_i(x, y)$ are gradient magnitudes of pixels that have discrete gradient orientations equal to $ori(i)$. An example of the orientation histogram is given in Figure1.
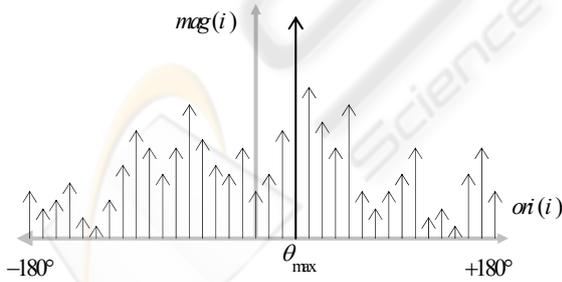

Figure 1: 36 bins orientation histogram constructed using local gradient data around a key-point.

The orientation of the SIFT feature is defined as the orientation corresponding to the maximum bin of the orientation histogram according to:

$$\theta_{max} = ori\left(\arg\max\left(mag(i)\right)\right) \qquad (5)$$

3. Feature Description: A local feature descriptor is computed at each key-point based on the local image gradient data. The region around the key-point is divided into 16 square boxes. For each box an eight bin orientation histogram is calculated from gradient data of pixels within the corresponding box relative to the feature orientation to provide rotation invariance. Finally, all 16 resulted eight bin orientation histograms is transformed into 128-D vector. The vector is normalized to unit length to achieve the invariance against illumination changes.

Therefore the original SIFT feature consists of four attributes, a location $P(x, y)$, a scale σ (level of scale space where is the key-point), an orientation θ_{max} and a 128-D descriptor vector V. Hence, the original SIFT feature can be written as:

$$F(P, \sigma, \theta_{max}, V).$$

3 EXTENDED SIFT FEATURES

Generally, if a scene is captured by two cameras or by one camera but from two different viewpoints, the corresponding points in two resulted images, which represent images of the same 3D point, will have different image coordinates, different scales, and different orientations, though, they must have almost similar descriptors which are used to match the images using a similarity measures.

In order to speed-up the features matching, it is assumed in this paper that two independent orientations can be assigned to each feature so that the angle ϕ between them stays almost unchanged for all correct corresponding points even in the case of the images captured under different conditions such as viewing geometry and illumination changes.

The idea of using an angle between two independent orientations is aimed at avoidance of comparison of a great portion of features that can not be matched in any way. This leads to a significant acceleration of the matching step. Hence, the reason for proposing SIFT feature angle ϕ is twofold.

On the one hand, to filter the correct matches, so that a correct match M_{ij} can be established between two features F_i^1 and F_j^2, which belong respectively to images 1 and 2, if and only if the difference between their angles ϕ_i^1 and ϕ_j^2 is less than a preset threshold value ε:

$$|\Delta\phi| = \left|\phi_i^1 - \phi_j^2\right| \leq \varepsilon \qquad (6)$$

On the other hand, the reason for proposing SIFT feature angle ϕ is to accelerate the SIFT feature matching because there is no necessity to compare two features if the difference between their angles is larger than a preset threshold ε.

3.1 Matching Speeded-Up Factor

Assuming two images to be matched whose feature angles $\left\{\phi_i^1\right\}$ and $\left\{\phi_j^2\right\}$ are considered as random variables Φ_1 and Φ_2 respectively.

In the case of correct matches the random variables Φ_1 and Φ_2 are dependent on each other since the angle differences of correct matches are equal to zero which correspond to the ideal image matching case.

In contrast, the random variables Φ_1 and Φ_2 are independent of each other for incorrect matches while the angle differences of incorrect matches are somehow distributed in the range $[-\pi, \pi]$.

Therefore, the difference $\Delta\Phi = \Phi_1 - \Phi_2$ for the incorrect matches has a probability density function (PDF) distributed over the whole angle range $[-\pi, \pi]$, whereas the PDF of $\Delta\Phi$ for the correct matches is concentrated in the so-called range of correct matches, which is the narrow range about $0°$.

Generally, if the random variables Φ_1 and Φ_2 are independent and uniformly distributed in the range $[-\pi, \pi]$, their difference $\Delta\Phi$ is uniformly distributed in the same range (Simon et al., 1995).

If a matching procedure, which compares only the features having angle differences $\Delta\Phi$ in the range of correct matches, is used in the case of uniform distribution of $\Delta\Phi$ for incorrect matches, then the matching process is accelerated by a speed-up factor SF. Speed-up factor can be expressed as the ratio between the width of the whole angle range $w_{total} = 360°$ and the width of the range of correct matches w_{cor}:

$$SF = \frac{w_{total}}{w_{cor}} = \frac{360°}{w_{cor}} \qquad (7)$$

3.2 SIFT Feature Angle

It is suggested that a SIFT feature is extended with an angle that meets the following conditions:
1- The angle has to be invariant to the geometric and photometric transformations (the invariance condition);
2- The angle has to be uniformly distributed in the range $[-\pi, \pi]$ (the "equally likely" condition).

To assign an angle to the SIFT feature, two orientations are required.

The invariance condition is guaranteed only if these orientations are different, whereas the "equally likely" condition is guaranteed if the orientations are independent and uniformly distributed in the range $[-\pi, \pi]$.

As mentioned in Section 2, the original SIFT feature has already an orientation θ_{max}. Therefore, it is only necessary to define one new orientation.

Firstly, the angle θ_{sum} corresponding to the vector sum of all orientation histogram bins is considered and the difference between the suggested orientation and the original SIFT feature orientation $\phi_{sum} = \theta_{sum} - \theta_{max}$ is assigned to the SIFT feature as the SIFT feature angle $\phi = \phi_{sum}$.
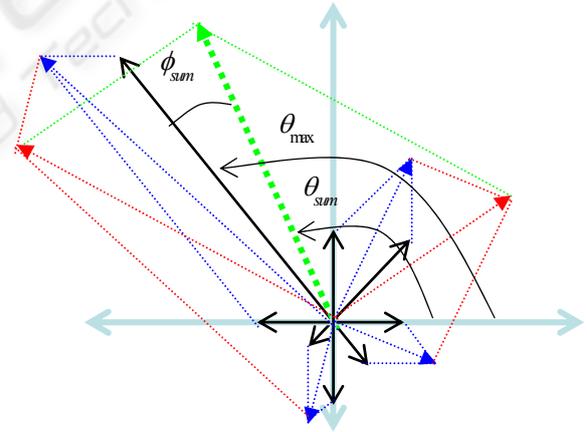

Figure 2: The vector sum of the bins of an eight orientation histogram.

Figure 2 presents geometrically the vector sum of an eight bins orientation histogram (eight bins only for the sake of simplicity), whereas the used orientation histogram has 36 bins as explained in Section 2 for the case of the original SIFT. Hence, mathematically, the proposed orientation θ_{sum} is calculated according to:

$$\theta_{sum} = \arctan\left(\frac{\sum_{i=-17}^{18} mag(i)\cdot\sin(ori(i))}{\sum_{i=-17}^{18} mag(i)\cdot\cos(ori(i))}\right) \qquad (8)$$

Since θ_{sum} is different from θ_{max}, ϕ_{sum} meets the invariance condition.

To examine whether ϕ_{sum} meets the "equally likely" condition, it is considered as a random variable Φ_{sum}.

The PDF of Φ_{sum} is estimated using 725356 SIFT features extracted from 600 test images (400 benchmark images (Image-Dataset) and 200 stereo images from a real-world robotic application) Some examples of used images are given in Section 5.

The PDF of Φ_{sum} was computed by dividing the angle space $[-180°,180°]$ into 36 sub-ranges, where each sub-range cover $10°$, and by counting the numbers of features whose angle ϕ_{sum} belong to each sub-range.

As evident from Figure 3 about 60% of features have angles ϕ_{sum} falling in the range $[-30°,30°]$. The reason of this outcome is the high dependency between θ_{max} and θ_{sum} due to the fact that the θ_{sum} corresponds to the vector sum of all orientation histogram bins including the bin which corresponds to θ_{max}.
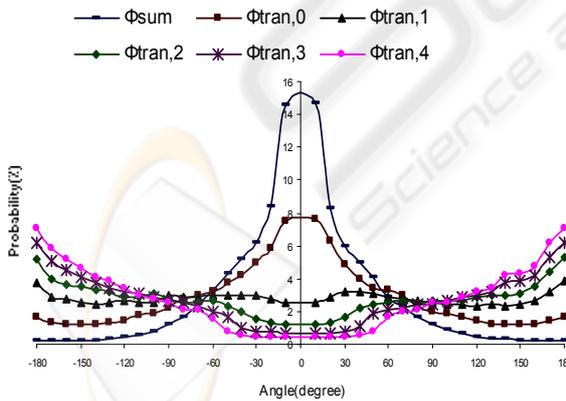

Figure 3: The experimental PDFs of Φ_{sum} and $\Phi_{tran,\kappa}$ for SIFT features extracted from 600 test images.

The θ_{max} is the dominant orientation in the patch around the key-point so that it has dominant influence to the θ_{sum}. Due to the high dependency

between θ_{max} and θ_{sum}, ϕ_{sum} does not meet the "equally likely" condition and can not be considered as SIFT feature angle.

To define an appropriate SIFT feature angle, orientations $\theta_{tran,\kappa}$ are further suggested These orientations are computed as the vector sums of all orientation histogram bins excluding the maximum bin and κ of its neighbour bins at the left and at the right side as follows:

$$\theta_{tran,0} = \arctan\left(\frac{\sum_{\substack{i=-17\\i\neq m}}^{18} mag(i)\cdot\sin(ori(i))}{\sum_{\substack{i=-17\\i\neq m}}^{18} mag(i)\cdot\cos(ori(i))}\right)$$

$$\theta_{tran,1} = \arctan\left(\frac{\sum_{\substack{i=-17\\i\notin[m-1,m+1]}}^{18} mag(i)\cdot\sin(ori(i))}{\sum_{\substack{i=-17\\i\notin[m-1,m+1]}}^{18} mag(i)\cdot\cos(ori(i))}\right) \qquad (9)$$

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$$\theta_{tran,\kappa} = \arctan\left(\frac{\sum_{\substack{i=-17\\i\notin[m-\kappa,m+\kappa]}}^{18} mag(i)\cdot\sin(ori(i))}{\sum_{\substack{i=-17\\i\notin[m-\kappa,m+\kappa]}}^{18} mag(i)\cdot\cos(ori(i))}\right)$$

where $m = \arg\max(mag(i))$.

The PDFs of the random variables $\Phi_{tran,\kappa}$ corresponding to angles $\phi_{tran,\kappa} = \theta_{tran,\kappa} - \theta_{max}$ are estimated in the same manner as the PDF of Φ_{sum}, performing the experiments over 725356 SIFT features extracted from the same 600 test images mentioned before. The measured PDFs of $\Phi_{tran,\kappa}$ (for $\kappa = 0,1,2,3,4$) are shown in Figure 3. It is evident from Figure 3 that the $\Phi_{tran,1}$ has a PDF which is the closest to the uniform distribution. Therefore, the angle $\phi_{tran,1}$ meets both conditions, invariance and "equally likely" condition, and it can be considered as a new attribute ϕ of the SIFT feature, $\phi = \phi_{tran,1}$. With this extension a SIFT feature becomes $F(P,\sigma,\theta_{max},V,\phi)$.

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4 SPLIT AND EXTENDED SIFT FEATURES MATCHING

Assuming that two sets of extended SIFT features are given:

$$R = \{F_i^r ; i = 1, 2, ..., r\}$$

$$L = \{F_j^l ; j = 1, 2, ..., l\},$$

containing respectively r and l features. The number of possible matches $M_{ij}\left(F_i^r, F_j^l\right)$ is equal to $r \cdot l$. Among these possible matches a small number of correct matches may exist. Considering of all possible matches is computationally expensive.

In the following two novel matching procedures are proposed to accelerate the matching process. The main idea behind both procedures is comparison of only features that share the same property which may lead to correct matches.

4.1 Split SIFT Features Matching

As said in Section 2, the SIFT feature locations are detected as the extrema of the scale space. Extrema can be Minima or Maxima so that there are two types of SIFT features, Maxima and Minima SIFT features.

Through the extraction of SIFT features from 600 different images in considered experiments, it was found that the number of Maxima is almost equal to the number of Minima SIFT features extracted from the same image. The matching time was reduced by 50% with respect to the original SIFT matching starting from the idea that no correct match can be expected between two features of different types. The claim that no correct matches between Minima and Maxima SIFT features is experimentally supported. Namely, it was found that the features of each correct match are always from the same type.

To declare the matching time reduction by splitting the SIFT features, it is assumed that the number of features extracted from the first and the second image are expressed as:

$$r = r_{\max} + r_{\min}$$
$$l = l_{\max} + l_{\min} \qquad (10)$$

where $r_{\max}(l_{\max})$ and $r_{\min}(l_{\min})$ are the numbers of Maxima and Minima SIFT features respectively.

The matching time without regard to the type of features, that is the time of exhaustive search, is:

$$T_{exh} = r \cdot l \qquad (11)$$

The matching time, in the case of comparison of only features of the same type, is proportional to the following sum:

$$T_{split} = r_{\max} \cdot l_{\max} + r_{\min} \cdot l_{\min} \qquad (12)$$

Substituting the assumption $r_{\max} \cong r_{\min} \cong r/2$ and $l_{\max} \cong l_{\min} \cong l/2$ into (12) one obtains:

$$T_{split} = r \cdot l / 2 = T_{exh}/2 \qquad (13)$$

Hence, the matching time is decreased by 50% in respect to exhaustive search.

4.2 Extended SIFT Features Matching

A set of SIFT feature angle differences $\{\Delta\phi_{ij} = \phi_i^r - \phi_j^l ; ij = 1, 2, ..., r \cdot l\}$ is established for the SIFT feature angles $\{\phi_i^r ; i = 1, 2, ..., r\}$ and $\{\phi_j^l ; j = 1, 2, ..., l\}$ of the extended SIFT features from the given sets R and L.

Considering the angle differences $\Delta\phi_{ij}$ as a random variable $\Delta\Phi_{ij}$, the PDFs of $\Delta\Phi_{ij}$ for both correct and incorrect matches are measured in experiments over considered 600 images.

The measured PDFs are shown in Figure 4. It can be seen from Figure 4 that about 92 % of correct and only 12% of possible matches belong to [-20°,20°]. Therefore, in order to find correct matches it is needed to treat only 12% of possible matches which can speed-up the features matching significantly.

To exploit this outcome, SIFT features are divided into several subsets based on their angles. The SIFT features of each subset are compared only with the features of some subsets, so that the resulting correspondences must have absolute differences of angles less than a pre-set threshold. Here a threshold of 20 is selected because almost all correct matches have angle differences in the range [-20°, 20°] as illustrated in Figure 4.

Consider that each of the sets of features R and L are divided into b subsets, so that the first subset contains only the SIFT features whose angles belong to $[-\pi, -\pi + 2\pi/b)$ and the ith subset contains features whose angles belong to $[-\pi + 2(i-1)\pi/b, -\pi + 2i\pi/b)$. Consequently, the

b^{th} subset contains features whose angles belong to $[-\pi + 2(b-1)\pi/b , \pi)$.
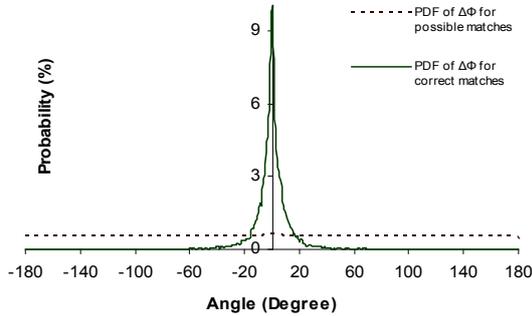

Figure 4: The experimental PDF of the angle difference for the incorrect and the possible matches.

The number of features of the both sets can be expressed as:

$$r = r_0 + r_1 + ... + r_{b-1}$$
$$l = l_0 + l_1 + ... + l_{b-1} \quad (14)$$

Because of the evenly distribution of feature angles over the range of their angles $[-\pi, \pi]$ as shown in Figure 3, the features are almost equally divided into several subsets. Therefore, it can be asserted that the feature numbers of each subset are almost equal to each other.

$$r_0 \cong r_1.... \cong r_{b-1} \cong r/b$$
$$l_0 \cong l_1.... \cong l_{b-1} \cong l/b \quad (15)$$

To exclude matching of features that have a difference of angles outside the range $[-a°, a°]$, each subset is matched to its corresponding one and to n neighbouring subsets to the left and to the right side as illustrated in Figure 5. In this case the matching time is proportional to the following term:

$$T_{extend} = \sum_{i=0}^{b-1}\left(r_i \cdot \sum_{j=i-n}^{j+n} l_j \right)$$
$$T_{extend} \cong \frac{r \cdot l}{b^2} \sum_{i=0}^{b-1}(1) \sum_{j=i-n}^{i+n}(1) \quad (16)$$
$$T_{extend} \cong \frac{r \cdot l \cdot (2n+1)}{b}$$

Therefore, the achieved speed-up factor to exhaustive search is equal to:

$$SF_{extend} = \frac{b}{2n+1} \quad (17)$$

The relation between n, a and b is as follows:

$$(2 \cdot n+1) \cdot \frac{360°}{b} = 2.a \Rightarrow n = \left\lfloor \left(\left(\frac{2 \cdot a \cdot b}{360} - 1 \right) \middle/ 2 \right) \right\rfloor \quad (18)$$

where $\lfloor \bullet \rfloor$ represents the first integer value larger than or equal to $\bullet$.

Substituting (18) into (17) yields:

$$SF_{extend} = \frac{360°}{2a} \quad (19)$$

The result (19) means that if it is aimed to exclude matching of features that have angle differences outside the range $[-20°, 20°]$, then the matching step is accelerated by a factor 9.

When this modification of original SIFT feature matching is combined with the split SIFT features matching, the obtained speedup factor is 18 without loosing a noticeable portion of correct matches. This is illustrated with the experimental results presented in the next section.
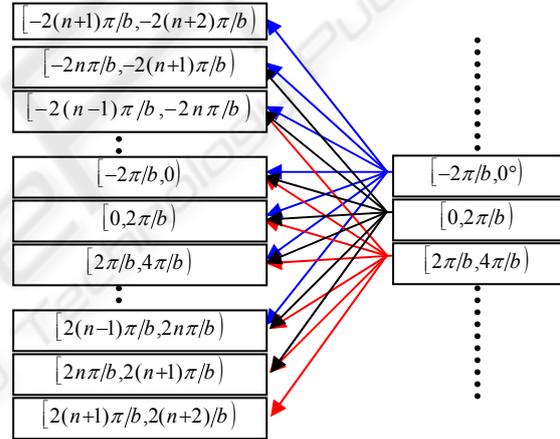

Figure 5: The matching procedure through the comparison of features having angle differences smaller than a pre-set threshold.

5 EXPERIMENTAL RESULTS

The proposed method for speeding up feature matching based on split and extended SIFT features was tested using both a standard image dataset, and real world stereo images.

The used image dataset *ID consists of about 500 images of 34 different scenes. Each scene is represented with a number of images taken under different photometric and geometric conditions. Some examples of the images used in the experiments, whose results are presented here, are given in Figure 6.

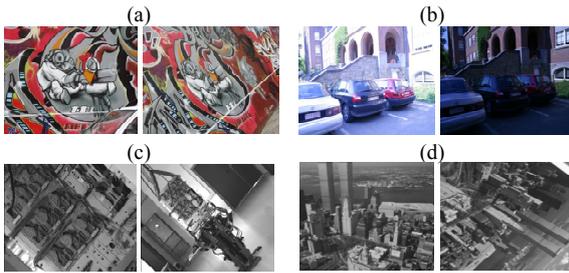Stereo images were grabbed by the stereo camera

Figure 6: Some of the standard dataset images of scenes captured under different conditions: (a) viewpoint, (b) light changes, (c) zoom, (d) rotation.

system of the rehabilitation robotic system FRIEND (Functional Robot arm with frIENdly interface for Disabled people) (Martens et al., 2007). FRIEND is intended to support the user in daily life activities which demand object manipulation such as serving a drink and preparing and serving a meal. The crucial for autonomous object manipulation is precise 3D object localization. The key factor for reliable 3D reconstruction of object points is correct matching of correspondence points in stereo images. Hence, stereo robot vision is a typical application where fast and reliable feature matching is of utmost interest.

Some examples of stereo images showing FRIEND environment in "serving a drink" robot working scenario are given in Figure 7.

In order to evaluate the effectiveness of the proposed method, its performance was compared with the performances of two algorithms for ANN (hierarchical k-means tree and randomized kd-trees).

Figure 7: Stereo images from a real-world robotic application used in the experiments.

Comparisons were performed using the Fast Library for Approximate Nearest Neighbors **(FLANN), which is a library for performing fast approximate nearest neighbour searching in high dimensional spaces. For all experiments, the matching process is carried out under different precision degrees making trade off between matching speedup and matching accuracy.

The precision degree is defined as the ratio between the number of correct matches returned using the considered algorithm and the number of correct matches returned using exhaustive search,

*http://lear.inrialpes.fr/people/Mikolajczyk/Database/index.html
**http://people.cs.ubc.ca/~mariusm/index.php/FLANN/

whereas the speedup factor is defined as the ratio between the exhaustive matching time and the matching time for the corresponding method

For both ANN algorithms, hierarchical k-means trees and randomized kd-trees, the precision is adjusted by the number of nodes to be examined, whereas for the proposed "Split and Extended SIFT" method, the precision is determined by adjusting the width of the range of correct matches w_{cor} (explained in Section 3). The correct matches are determined using the Nearest Neighbor Distance Ratio matching strategy (Lowe, 2004) with distance ratio equal to 0.6, followed by RANSAC algorithm to keep only inliers.

Two experiments were run to evaluate proposed method, on real stereo images and on the images of the dataset ID. In the first experiment, SIFT features are extracted from 200 stereo images. Each two corresponding images are matched using all three considered algorithms under different degrees of precision. The experimental results are shown in Figure 8.
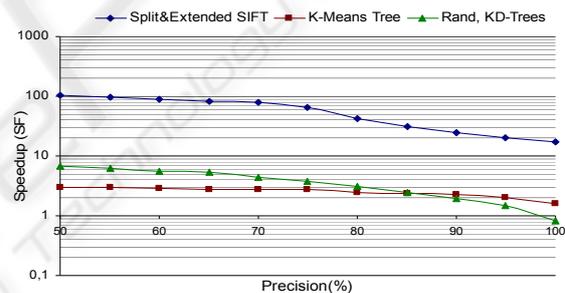

Figure 8: Trade-off between matching speedup and matching precision for real stereo image matching.

As can be seen from Figure 8, the performance of the proposed method outperforms both ANN algorithms for all precisions. For precision around 99% level, the proposed method provides a speedup factor of about 20. For the lower precision degree speedup factor is much higher.

As evident from Figure 8 by using proposed "Split and extended SIFT" the speedup factor relative to exhaustive search can be increased to 80 times while still returning 70% of the correct matches.

The second experiment was carried out on the images of the dataset ID. As said before, this dataset consists of about 500 images of various contents. These images represent images of 34 different scenes taken under different conditions such as rotation, zoom, light and viewpoint changes.

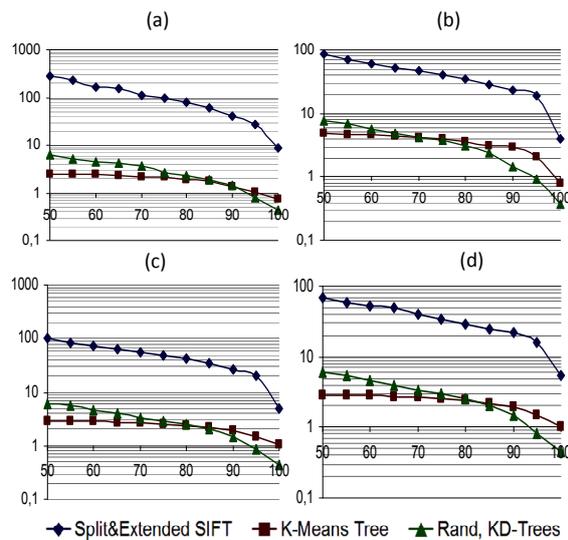For the performed experiments the images of dataset are grouped according to these different con-

Figure 9: Trade-off between matching speedup (SF) and matching precision for image groups (a) light, (b) viewpoint, (c) rotation, (d) zoom changes.

ditions into viewpoint, zoom, rotation and light group. For each group, SIFT features are extracted from each image and pairs of two corresponding images are matched using hierarchical k-means tree, randomized kd-trees and proposed "Split and Extended SIFT", with different degrees of precision. The experimental results are shown in Figure 9.

As evident from Figure 9, proposed "Split and Extended SIFT" outperforms the both other considered ANN algorithms in speeding up of features matching for all precision degrees.

6 CONCLUSIONS

In this paper two novel ideas are proposed to accelerate the matching process. Both ideas are based on the same principle, which is comparison of only features that share the same property which may lead to correct matches. The proposed method was compared with two algorithms for ANN searching, hierarchical k-means and randomized kd-trees. The presented experimental results show that the performance of the proposed method outperforms two other considered algorithms. Also, the presented experimental results show that the feature matching step can be accelerated 18 times with respect to exhaustive search without losing a noticeable portion of correct matches. When only 50% of correct matches is required, the speedup factor can be increased to more than100.

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