

# Color Supported Generalized-ICP

Michael Korn, Martin Holzkothén and Josef Pauli

*Lehrstuhl Intelligente Systeme, Universität Duisburg-Essen, 47057 Duisburg, Germany*

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**Abstract:** This paper presents a method to support point cloud registration with color information. For this purpose we integrate  $L^*a^*b^*$  color space information into the Generalized Iterative Closest Point (GICP) algorithm, a state-of-the-art Plane-To-Plane ICP variant. A six-dimensional  $k$ -d tree based nearest neighbor search is used to match corresponding points between the clouds. We demonstrate that the additional effort in general does not have an immoderate impact on the runtime, since the number of iterations can be reduced. The influence on the estimated 6 DoF transformations is quantitatively evaluated on six different datasets. It will be shown that the modified algorithm can improve the results without needing any special parameter adjustment.

## 1 INTRODUCTION

The Iterative Closest Point (ICP) algorithm has become a dominant method for dealing with range image aligning in the context of 3D Reconstruction, Visual Odometry and Self Localisation and Mapping (SLAM). Especially over the last three years, it has gained in popularity as range cameras have become low priced and highly available for everyone. However, since it usually relies only on geometry, this algorithm has its weaknesses in environments with little 3D structure or symmetries. Fortunately, many of the new range cameras are equipped with a color sensor – as a consequence, the logical step is to improve the ICP algorithm by using texture information. To preserve the advantages of ICP – simplicity and performance – we are interested in integrating colors directly into the ICP algorithm. Alternatively, for example it is equally conceivable to estimate an initial alignment in a preprocessing step via Scale Invariant Feature Transform (SIFT) as described in (Joung et al., 2009). Although such an extension to ICP has been at the core of several research efforts, there is still no satisfactory answer as to how ICP should actually be combined with color information. In (Johnson and Kang, 1999), the distance function for the nearest neighbor search of a traditional ICP is extended by color information. In a similar approach (Men et al., 2011) use just the hue from the Hue-Saturation-Lightness (HSL) model to achieve illumination invariance. In (Druon et al., 2006), the geometry data is segmented by associated color in the six color classes red, yellow, green, cyan, blue and magenta. In ac-

cordance with a valuation method, the most promising class is then chosen to solve the registration problem. Nevertheless, the possibilities of said ICP and color information combination have not been conclusively investigated yet. Especially recent ICP variants should be considered.

This paper presents a way to integrate color information represented in  $L^*a^*b^*$  color space into Generalized-ICP (GICP), a state-of-the-art variant of the ICP algorithm. We focused on the question, how far this Plane-To-Plane ICP algorithm can benefit from color information and to what extent the runtime will be effected.

Section 2 summarizes some required background knowledge, 3 describes our modifications to GICP, 4 details our experiments and results. In the final section we discuss our conclusions and future directions.

## 2 BACKGROUND

We will introduce essential background knowledge with regard to GICP and our modifications. In particular, the characteristics of a Plane-To-Plane ICP will be considered.

### 2.1 ICP Algorithm

The Iterative Closest Point (ICP) algorithm was developed by Besl and McKay (Besl and McKay, 1992) to accurately register 3D range images. It aligns two point clouds by iteratively computing the rigid trans-

formation between them. Over the last 20 years, many variants have been introduced, most of which can be classified as affecting one of six stages of the ICP algorithm (Rusinkiewicz and Levoy, 2001):

- **Selection** of some set of points in one or both point clouds.
- **Matching** these points from one cloud to samples in the other point cloud.
- **Weighting** the corresponding pairs appropriately.
- **Rejecting** certain pairs based on looking at each pair individually or considering the entire set of pairs.
- Assigning an **error metric** based on the point pairs.
- Solving the **optimization** problem.

Since all ICP variants might get stuck in a local minimum, they are generally only suitable if the distance between the point clouds is already small enough at the beginning. This insufficiency is often handled by estimating an initial transformation with methods or algorithms that converge to the global minimum but with lower precision. Following this procedure, an ICP algorithm is then used to improve the result by performing a *Fine Registration* (Salvi et al., 2007). In other scenarios, no guess of the initial transformation is needed because the difference between the measurements is sufficiently small. In many applications, the point clouds are created and processed at such a high rate (up to 30Hz) that this precondition is met.

The simplest concept based on (Besl and McKay, 1992) with an improvement proposed by (Zhang, 1994) is illustrated in 1 and is often referred to as *Standard ICP* (cf. (Segal et al., 2009)). The algorithm requires the model point cloud  $A$  and the data point cloud  $B$  in order to estimate the transformation  $T$  between them. Additionally, a rough estimate transformation  $T_0$  can be considered. If the unknown, true transformation between the point clouds is small enough, the initial transformation can be set to the identity.

In every iteration, each of the  $N$  points of the data point cloud is transformed with the current transformation estimation and matched with its corresponding point from the model  $A$  (line 4). Matches are rejected if the Euclidean distance between the pairs exceeds  $d_{max}$ , by setting the weight to 0 or 1 accordingly. After solving the optimization problem in line 11, the next iteration starts. Usually the algorithm converges if the difference between the estimated transformation of two subsequent iterations becomes small or if a predefined number of iterations is reached.

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**Algorithm 1:** Standard ICP.
 

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**Input:** Pointclouds:  $A = \{a_1, \dots, a_M\}$ ,  $B = \{b_1, \dots, b_N\}$   
 [0] An initial transformation  $T_0$

**Output:** The transformation  $T$  which aligns  $A$  and  $B$

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1:  $T \leftarrow T_0$ 
2: while not converged do
3:   for  $i \leftarrow 1$  to  $N$  do
4:      $m_i \leftarrow \text{FindClosestPointInA}(Tb_i)$ 
5:     if  $\|m_i - Tb_i\|_2 \leq d_{max}$  then
6:        $w_i \leftarrow 1$ 
7:     else
8:        $w_i \leftarrow 0$ 
9:     end if
10:  end for
11:   $T \leftarrow \underset{T}{\operatorname{argmin}} \sum_i w_i \|Tb_i - m_i\|_2^2$ 
12: end while
  
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## 2.2 GICP Algorithm

The Standard ICP algorithm is a Point-To-Point approach, which means that it tries to align all matched points exactly by minimizing their Euclidean distance. This doesn't take into account that an exact matching is usually not feasible because the different sampling of the two point clouds leads to pairs without perfect equivalence. 1 illustrates two point clouds, both being different samplings of the same scene. The

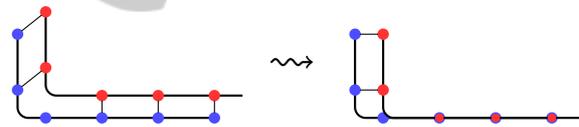


Figure 1: The exact Point-To-Point matching of the Standard ICP can lead to a poor alignment of two samplings (blue and red point clouds) of the same scene.

right part of this figure shows the result when applying Standard ICP. Three of the correspondences have a distance close to zero while the other two pairs still have a significant offset – reducing it could improve the result. Obviously, the red data cloud should be shifted to the left for a perfect alignment, but this would increase three of the pairs' distances while reducing only two, which would deteriorate the result in terms of the strict Point-To-Point metric.

To overcome this issue, some variants of ICP take advantage of the surface normal information. While Point-To-Plane variants consider just the surface normals from the model point cloud, Plane-To-Plane variants use the normals from both model and data point cloud. The Generalized-ICP (GICP) algorithm introduced in (Segal et al., 2009) belongs to the second category. It uses a probabilistic model to modify the error function in line 11 of 1 by assigning a covariance matrix to each point. This is based on the

assumption that every measured point results from an actually existing point and the sampling can be modeled by a multivariate normal distribution. The outcome of the derivation in (Segal et al., 2009) is the new error function

$$\mathbf{T} \leftarrow \underset{\mathbf{T}}{\operatorname{argmin}} \sum_i d_i^{(\mathbf{T})T} (C_i^A + \mathbf{T} C_i^B \mathbf{T}^T)^{-1} d_i^{(\mathbf{T})} \quad (1)$$

where  $d_i^{(\mathbf{T})} = a_i - \mathbf{T}b_i$  with covariance matrices  $C_i^A$  and  $C_i^B$  (assuming that all points which could not be matched were already removed from  $A$  and  $B$  and that  $a_i$  corresponds with  $b_i$ ). This formula resembles the Mahalanobis distance – only the square root is missing. An appropriate selection of  $C_i^A$  and  $C_i^B$  can reproduce the error function of the Standard ICP or a Point-To-Plane variant (Segal et al., 2009). It is proposed to use the covariance matrix

$$\begin{pmatrix} \varepsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

for a point with the surface normal  $e_1 = (1, 0, 0)^T$ , where  $\varepsilon$  is a small constant representing the covariance along the normal. In general, this covariance matrix must be rotated for every point depending on its surface normal. In 2, the covariance matrices are visualized as confidence ellipses: The position of a point is known with high confidence along the normal, but the exact location in the plane is unsure.

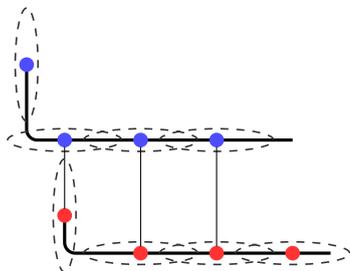


Figure 2: The confidence ellipses show how the probabilistic Plane-To-Plane model of the Generalized-ICP works.

We have decided to build on GICP because we expect to get better results compared with other ICP variants. Particular worthy of mention is the low sensitivity to the choice of the distance  $d_{max}$  (line 5 of 1). In general, if  $d_{max}$  is selected too small, the probability of convergence to an entirely wrong local minimum is high and the number of iterations may go up. For  $d_{max} \rightarrow \infty$ , the estimated transformation increasingly loses accuracy, yet GICP still shows a better robustness in comparison with Standard ICP. There is a direct connection to the observation that an ICP algorithm works best if the data point cloud

is a subset of the model point cloud. It may happen that the data cloud contains points with no adequate correspondence in the model due to missing points caused by occlusion or a slight offset of the measured area. Nevertheless, many ICP variants consider these points until the distance of the false pairs exceeds  $d_{max}$ , whereas in GICP this effect is automatically reduced since such points often lie on a plane and the distance along the surface normal is very small.

## 2.3 L\*a\*b\* Color Space

The data from color cameras is usually provided in an RGB color space. Unfortunately, this color model is not well-suited to determine the difference between colors because it is not perceptually uniform. This means that the Euclidean distance between two RGB colors is not proportional to the perceived difference of these colors (Paschos, 2001). In 1976, the International Commission on Illumination (CIE) introduced the L\*a\*b\* color space (or CIELAB), which is a color-opponent space with dimension L\* for lightness and a\* and b\* for the color-opponent dimensions. 3 illustrates how the a\* axis corresponds to red-green proportion and the b\* axis determines yellow-blue proportion. The L\*a\*b\* color space aspires to perceptual

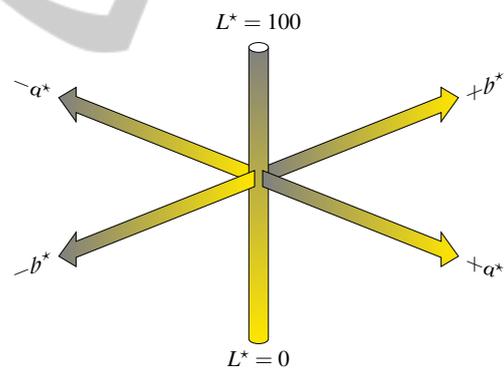


Figure 3: Illustration of the L\*a\*b\* color space.

uniformity and is also appropriate to deal with high illumination variability (Paschos, 2001) (Macedo-Cruz et al., 2011).

## 3 INTEGRATING COLOR

The GICP is a promising approach and we decided to build on it. Because of the significance of the Euclidean distance, it makes sense to combine the L\*a\*b\* color space with a geometric based algorithm. There are several possibilities to integrate color information into GICP. According to the list in subsection

2.1, the steps *selection*, *matching*, *weighting*, *rejection* and the error metric could be improved.

We have major doubts to modify the selection step as in (Druon et al., 2006); the division of both point clouds into different color classes leads to an extreme thinning of the clouds and therefore an inadmissible loss of information. Weighting or rejecting point pairs based on their colors could depreciate wrong correspondences, but this doesn't automatically promote the creation of better correspondences. Maybe this could increase the dominance of good pairs. In any case, the number of considered pairs would be reduced. This can be problematic, as particularly during the first iterations of GICP, many correspondences are wrong, but serviceable for converging to the correct solution.

An interesting idea is to include the color information into the error metric. Unfortunately, this would go beyond the concept of an ICP algorithm. By reducing the geometric distance of point pairs, it is not possible to reduce the color distance of the pairs. Consequently, it would no longer be enough to consider just point pairs.

We have selected the matching step to realize our modification. This is one of the most crucial steps of the ICP algorithm regarding the quality of the final registration. The future stages of the algorithm are largely dependant on this step, since a high number of incorrectly associated points obviously cannot lead to a good registration result.

One of the main advantages of Standard ICP is its simplicity, which allows to use very efficient data structures for its matching step, namely *k*-d-trees (Bentley, 1975). Since we want to retain this benefit, we chose to simply extend the problem of finding the nearest neighbor from a three-dimensional to a six-dimensional space, which includes three additional components for  $L^*a^*b^*$  color values. As a consequence, a point has the following structure:

$$p_i = (x_i \ y_i \ z_i \ L_i \ a_i \ b_i)^T$$

Since there is no natural relation between position and color distance, we introduce a *color weight*  $\alpha$ :

$$p_{\alpha,i} = (x_i \ y_i \ z_i \ \alpha L_i \ \alpha a_i \ \alpha b_i)^T.$$

The weight  $\alpha$  also serves as scale between geometric distance of the points and color distance to ensure that they are in the same order of magnitude. Since the matching is still based on the Euclidean distance

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2 + \alpha^2 ((L_i - L_j)^2 + (a_i - a_j)^2 + (b_i - b_j)^2)}$$

between points  $p_{\alpha,i}$  and  $p_{\alpha,j}$ , the correspondences can be determined by a nearest neighbor search using a

*k*-d tree, where  $\alpha$  affects the priority of the color differences. For  $\alpha = 0$ , the resulting transformation exactly equals the output of the original GICP.

The choice of the right weight depends very much on the sensor hardware. The scale part of  $\alpha$  can be determined relatively easily. To get a first idea of the scale, the metric (meter or millimeter) of the range images must be considered and whether the sensor works in close-up or far range. But a good choice of the weight also depends on range image and color image noise.

## 4 EVALUATION AND RESULTS

We evaluated the color supported Generalized-ICP with six datasets from (Sturm et al., 2012) and one self-created point cloud pair. All datasets were obtained from a Microsoft Kinect or an Asus Xtion camera and  $d_{max} = 0.2$ m was used for all examined scenes. The datasets from (Sturm et al., 2012) include highly accurate and time-synchronized ground truth camera poses from a motion capture system, which works with at least 100Hz and up to 300Hz.

Our implementation uses the Point-Cloud-Library (PCL) (Rusu and Cousins, 2011). The PCL already contains a GICP implementation which is strictly based on (Segal et al., 2009) and also offers the possibility of modification. We measured the runtimes on an Intel Core i7-870 with PC1333 DDR3 memory without any parallelization. The runtimes do not include the application of the voxel grid filter<sup>1</sup>, but they consider the transformation of the color space. To guarantee a fair comparison, we always applied the unmodified GICP for  $\alpha = 0$ . We removed points from all point clouds with a Z-coordinate greater than 3m, because we observed that the noise of points with a greater distance generally degrades the results, regardless of the color weight.

For the quantitative assessment, we determined the transformations between the point clouds of the different datasets. To avoid incorporating another algorithm for *Coarse Registration*, the temporal offset between the aligned point clouds was chosen small enough to use the identity as the initial transformation.

In the following evaluation, we will first of all examine the influence of the color weight. After that, we will evaluate the benefit of our modifications.

<sup>1</sup>A 3D voxel grid is created over a point cloud. All the points located in the same cell will be approximated with their centroid and their average color.

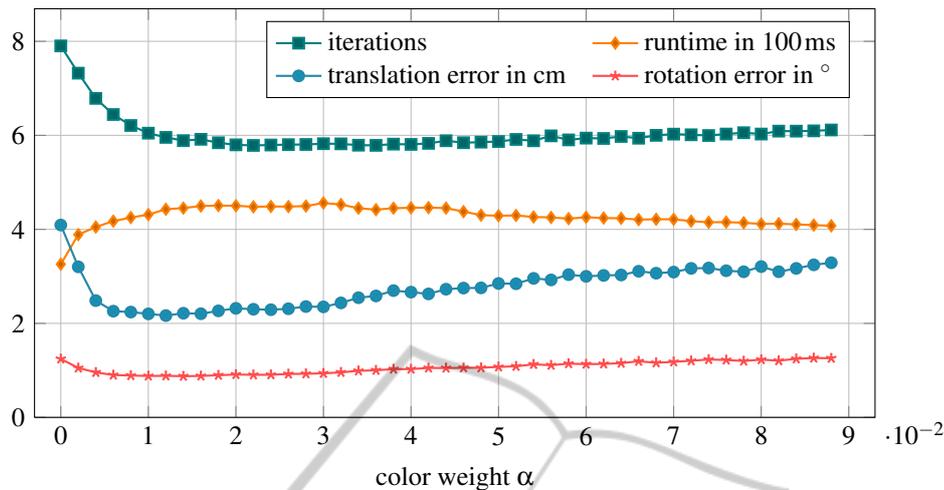


Figure 5: Influence of color weight on number of iterations, runtime, translation error and rotation error. Average values of 1977 aligned point cloud pairs from 'freiburg2\_desk' (a typical office environment with a lot of geometric structure).



Figure 4: Dataset 'freiburg2\_desk' from (Sturm et al., 2012) containing a typical office scene.

#### 4.1 Evaluating Color Weight

In a typical scene captured with the Kinect, the maximum  $L^*a^*b^*$  color space distance is approximately 120 and the geometric distance of the furthest points is about 3.5m. Apart from that, one must consider that the geometric distance of matched point pairs is smaller than 0.2m and the maximum color distance in a local area is approximately 40. As a consequence, the scale part of the color weight  $\alpha$  (which ensures color and geometric distances are in the same order of magnitude) should be roughly in the range of 0.005 to 0.029. 4 was taken from the sequence 'freiburg2\_desk'. The Kinect was moved around a typical office environment with two desks, a computer monitor, keyboard, phone, chairs, etc. We applied our color supported GICP to this dataset with different color weights. The cell size of the voxel grid filter is 2cm and the frame offset is 1s (every 30<sup>th</sup> frame). 5 illustrates the influence of  $\alpha$  on the number of iterations, runtime, translation error and rotation error. The results represent the average of 1977 registered point cloud pairs. A minimum of translation and rotation errors is located in the expected range. The color supported GICP is not too sensitive to a perfect choice

of  $\alpha$  since a wide range of  $\alpha$  values can be used to improve the results.  $0.006 \leq \alpha \leq 0.03$  seems to be a good choice. Furthermore, a reduction of the number of iterations can be observed due to better point matchings even in early iterations. However, as a consequence of the more complex algorithm, the runtime becomes worse, but considering the reduced errors it is still acceptable. A peculiarity is depicted at the beginning of the curves in 5. Although the number of iterations is decreasing, the runtime is extending. This highlights that the convergence of the optimization process (Broyden-Fletcher-Goldfarb-Shanno method which approximates Newton's method) has a large impact on the runtime. The optimization takes longer with a well-chosen color weight, since the algorithm performs greater adjustments of the transformation in every iteration. Nevertheless, the final transformation is closer to the reference and the errors are smaller.

It can be noted that even in a scene with sufficient geometric structure – where one could expect no appreciable advantage of using color information – the errors can still be reduced.

In contrast to the previous scene with plenty of geometric information, 7 shows the influence of  $\alpha$  for an environment without any structure (shown in 6). No voxel grid filter has been used and the frame offset is  $\frac{1}{3}$  s (every 10<sup>th</sup> frame). In the dataset 'freiburg3\_nostructure\_texture\_far', the Asus Xtion is moved in two meters height along several conference posters on a planar surface. As expected, the use of color information leads to a significant improvement of the results. Since the original GICP needs an unusually large number of iterations to converge, the color supported GICP even has a lower runtime. This is because the original GICP often drifts to a wrong

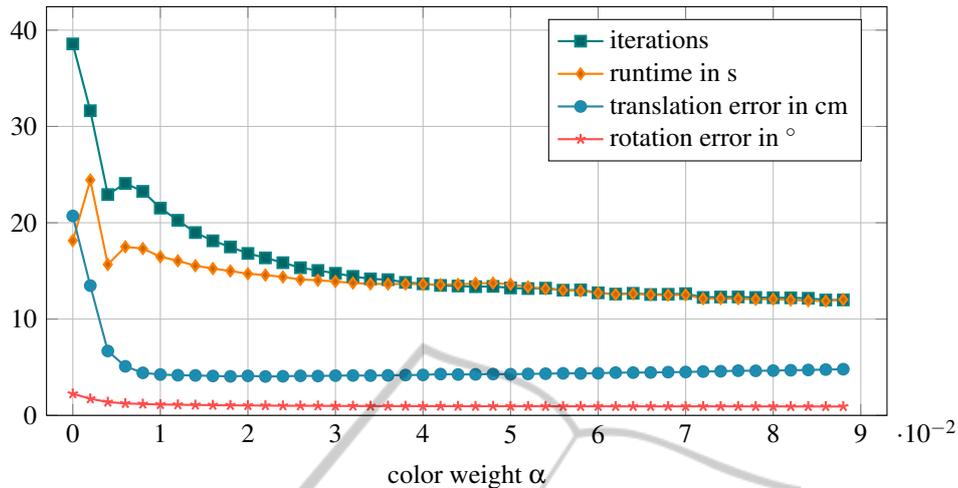


Figure 7: Influence of color weight on number of iterations, runtime, translation error and rotation error. Average values of 279 aligned point cloud pairs from 'freiburg3\_nostructure\_texture\_far' (planar surface with posters).



Figure 6: Dataset 'freiburg3\_nostructure\_texture\_far' (left) and 'freiburg3\_nostructure\_texture\_near\_withloop' (right).



Figure 8: Dataset 'freiburg1\_room' containing a typical office room with much motion blur due to fast movement.

direction, which is also indicated by the huge translation errors. Surely, this can be a peculiarity of the dataset and should not be generalized. The drift can be explained with range image noise. The application of a voxel grid filter can significantly reduce this drift and therefore the number of iterations and resulted errors decrease.

Overall, the curves decrease very early and stagnate at a lower level, because a small color weight is already sufficient to the color information becomes dominant over the range image noise. In the absence of geometric features, the sensitivity to the choice of the color weight is less than in the previously discussed dataset. As the color information becomes more important, the color weight should be higher. With respect to all examined datasets, a good choice is  $\alpha = 0.024 \pm 0.006$ .

## 4.2 Benefit of Color Support

In addition to the two scenes of the previous subsection, the suitability of color support will be shown for other scenes and for different cell sizes of the voxel grid filter. In order to preserve a better overview, the color weight will be set to a fixed value of  $\alpha = 0.024$

for all experiments in this subsection. The results are summarized in 1 and will be explained and discussed in the remainder of this section. The first dataset was already discussed above. Both the original GICP and the color supported GICP benefit from the voxel grid filter. It is noticeable, though, that the effect on the modified GICP is smaller, which can be explained by the negative influence of smoothing the color information.

The next dataset was chosen to indicate the effects of fast camera movements, particularly as this often causes more problems for the color images as for the range images. This dataset was produced in a typical office room and is shown in 8. The camera was moved at high speed on a trajectory through the whole office. Therefore, a major part of the color images contains a lot of motion blur. Nevertheless, using color information improves the results, however, sharp images would probably have a stronger effect.

In the next two sequences (depicted in 6), the camera was moved along a textured, planar surface. In one case, which was already considered in the previous subsection, the height was two meters and in the other case it was one meter. In this scene the voxel grid filter has a particularly significant impact on the

Table 1: Comparison of the original GICP and the color supported GICP with  $\alpha = 0.024$  based on average values of number of iterations, runtime, translation error and rotation error. Six datasets (names were shortened) from (Sturm et al., 2012) and one self-created point cloud pair are considered under different cell sizes of the voxel grid filter ('-' means no voxel grid filter was used).

dataset (pairs, time offset)	voxel grid cell size (cm)	iterations		runtime (ms)		error (cm / °)	
		GICP	color GICP	GICP	color GICP	GICP	color GICP
freiburg2_desk (1977, 1s)	-	17.05	11.85	15544	22501	8.590 / 2.984	4.105 / 1.707
	2	7.90	5.79	322	444	4.093 / 1.244	2.290 / 0.907
	3	7.13	5.52	136	176	3.876 / 1.167	2.520 / 0.992
freiburg1_room (1323, 1/3s)	-	17.54	14.50	40797	72732	14.987 / 5.543	11.047 / 4.443
	2	11.54	9.56	479	770	14.963 / 4.559	10.801 / 3.225
	3	10.85	8.92	176	256	15.079 / 4.348	10.713 / 3.238
f3_nostructure_texture_far (279, 1/3s)	-	38.57	15.86	18199	14689	20.710 / 2.250	4.061 / 1.003
	2	4.87	5.32	262	411	10.313 / 0.966	7.507 / 0.939
	3	3.84	3.87	114	152	10.224 / 0.958	8.331 / 0.980
f3_nostructure_texture_near (1565, 1/2s)	-	6.14	10.27	5140	15101	12.755 / 3.485	8.727 / 2.440
	2	2.88	3.49	89	130	12.405 / 3.497	10.859 / 3.326
	3	2.71	3.12	39	53	12.356 / 3.506	11.102 / 3.402
f3_structure_texture_far (837, 1s)	-	9.43	6.85	7463	9864	2.640 / 0.563	1.776 / 0.522
	2	5.15	4.29	304	386	2.334 / 0.459	1.635 / 0.445
	3	4.64	3.88	132	159	2.388 / 0.460	1.987 / 0.452
f3_structure_texture_near (974, 1s)	-	10.036	9.02	22442	28145	4.793 / 1.040	4.003 / 0.988
	2	6.44	6.10	175	275	5.548 / 1.261	5.248 / 1.104
	3	5.76	5.64	70	102	5.679 / 1.222	5.573 / 1.195
office corridor (1, 21.6cm / 4°)	-	8	10	9057	20987	18.705 / 0.976	1.691 / 1.850
	2	8	7	565	865	16.959 / 0.764	1.854 / 0.336
	3	7	8	220	325	17.109 / 1.383	1.241 / 0.564



Figure 9: Dataset 'freiburg3\_structure\_texture\_far' (left) and 'freiburg3\_structure\_texture\_near' (right).

number of iterations and the runtime. Lower range image noise and less points lead to sooner convergence and – in case of two meters height – a shorter drift. Apart from suppressing the drift, the voxel grid filter has no impact on the original GICP since (independently of the smoothing) there is no useful structure information. A greater cell size of the voxel grid filter degrades the result of the color GICP since it removes too much valuable information.

Because of reducing the errors on 'freiburg2\_desk' with color information, the evaluation also includes the next two datasets shown in 9. The color-supported GICP can only slightly improve the results because the scene contains an unusually distinctive 3D structure that occurs very rarely in real applications.

Finally, a self-created point cloud pair has been captured in an office corridor, representing a more



Figure 10: The first row shows two point clouds of an office corridor. The lower row depicts their alignment with the original GICP (left) and with color support (right).

common case, in which the original GICP fails to reach a good alignment (see 10). This scene conveys only enough structural information to restrict three of the total six degrees of freedom. The alignment could still be rotated and translated like two ordinary planes without significantly affecting the error in terms of the plane-to-plane metric. The integration of colors, however, leads to a remarkable improvement.

Overall, the color supported GICP achieves a re-

duction of the average error. The concrete benefit depends on the scene, but considering only the accuracy of the estimated transformation there are no disadvantages. In most cases, the runtime rises, but this is moderated due to the reduction of the number of iterations.

## 5 CONCLUSIONS

In this paper, we present a method to integrate color information directly into the GICP algorithm. Due to the type of modification, only one new parameter has to be set and it was possible to give a general recommendation that shows good results in various scenes. It has been demonstrated that the estimated transformations are generally more accurate and the number of iterations is reduced, even though the runtime rises. Color support was shown to be particularly worthwhile in environments with texture and less 3D structure. Consequently, switching between the original and the modified GICP depending on the presence of structure features is reasonable. A negative impact on the resulting transformations could not be observed during the experiments, not even if the color images had a poor quality due to motion blur.

Compared to (Johnson and Kang, 1999) and (Men et al., 2011), the GICP benefits less from color integration than the Standard ICP algorithm. This can be explained in part by comparing GICP with Standard ICP: The measured translation and rotation errors of the Standard ICP on all examined structured scenes are approximately twice as high as those of GICP. And since GICP already performs much better, the benefit of any modification will be less in absolute terms. In addition, GICP reduces the distances of corresponding points in the direction of the surface normals. While the information obtained from the 3D structure is useful to correct the point alignments along the surface normals, the color information is helpful to align the points along the surfaces.

For future work, we plan to extend the error metric and thus also the concept of the GICP to allow structure features and color features to act in different directions.

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