Parallel implementation of hybridICP data registration

(Implementacja algorytmu dopasowania danych hybridICP z wykorzystaniem obliczeń równoległych)

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In this paper new implementation of On-Line data registration method is shown. Algorithm is using composition of classical approaches point to point and point to plane to achieve better convergence compared to single methods. To improve the performance the parallel computing based on NVIDIA CUDA capabilities is used mainly for k-nearest neighborhood search. Many research has been done concerning 3D data registration. It is easy to find on opinion that point to plane method is better in case of accuracy than point to point method. In theory it is true, but in real application such mobile robot moving in INDOOR environment equipped with commercial available 3D measurement system there are several exceptions. In this paper we are focused on real application and we demonstrate disadvantages of point to plane method that affect the aligning accuracy. The problems are related to the approximation accuracy that appear in data containing stairs, corners etc.

The main contributions of this paper are:

- new implementation of hybridICP data registration algorithm based on composition of classical approaches point to point and point to plane,
- improvement based on parallel computation applied mainly for k-nearest neighbor search
- empirical evaluation based on data set delivered by mobile robot equipped with commercial available 3D laser measurement system working in INDOOR environment.

Related Work

Most range data registration techniques are variants on the iterative closest point (ICP) algorithm, proposed by Chen and Medioni in [3] and Besl and McKay in [4]. We can find also an alternative solution to ICP for data alignment [12]. Point to plane approach is known to be the most accurate [1, 11, 13, 15, 17]. The combination of the point to point and point to plane algorithms into a single probabilistic framework is introduced in [2], it allows for the noise measurement and other probabilistic techniques to increase robustness in contrary to standard ICP. To avoid ICP tendency to converge to sub-optimal or incorrect solutions an evolutionary registration algorithm which does not require initial pre-alignment and has a very broad basin of convergence is proposed in [5]. The methodology for comparison of ICP variants are shown in [17]. Several tools are provided to select scenarios for validating results and to validate point to facet distance, correspondence and pose estimation individually. In addition to this, work [10] provides tools for analyzing robustness, precision, computational time and robustness sensibility to parameter variation. A review of recent range image registration methods with accuracy evaluation is shown in [14]. Another point to plane ICP variant is demonstrated in [6], where practical application of robot moving in plane – reach environment is shown. In [8] the generalization of the metric-based ICP(MbICP) [7] to three dimensional workspaces is shown. The emphasis of the work is on the development of all the mathematical formulation required to address the scan matching problem in three dimensional workspaces based on this new metric. In [9] the optimization framework using the squared distance function is proposed where point-to-point and point-to-plane ICP variants are reduced to two special cases of the general minimization problem.

Fast searching algorithms such as the k-d tree algorithm are usually used to improve the performance of the closest point search [18, 19]. GPU accelerated Nearest Neighbor Search for 3D Registration is proposed in [20], where the advantage of Arya's priority search algorithm described in [21] to fit NNS in the SIMD (Single instruction Multiple Data) model was used for GPU (Graphic Processing Unit) acceleration purpose. It was shown in [22] that k-d tree and priority queue methods are efficient but difficult to be implemented on GPU. In [23] a brute force NNS approach using CUDA shows that it is 400 times faster than CPU k-d tree approach. It is important to emphasize that the GPU-ICP performance up to 88 times for 68229 points compared to kd-tree based sequential CPU-ICP algorithm was shown and it takes 280 ms. GPU-based NNS with advanced search structures are also used in the context of ray tracing [24], where NNS procedure builds trees with a different manner from a triangle soup, and takes these triangles as the objects of interest. To convert k-d tree into serialized at array that can be easily loaded into CUDA device left-balanced k-d tree is proposed [25].

Point to point and point to plane data registration

Range images are defined as a model set M (reference points) and data set D (points to align), where N_m and N_d denotes the number of the elements in the respective set. The alignment of these two data sets for point to point ICP is solved by minimization of the following cost function:

$$E = (\mathbf{R}, \mathbf{t}) = \sum_{i=1}^{N_m} \sum_{j=1}^{N_d} w_{ij} \left\| \mathbf{m}_i - (\mathbf{R}\mathbf{d}_j + \mathbf{t}) \right\|^2 \qquad (1)$$

w_{ij} is assigned 1 if the i-th point of M correspond to the j-th point in D. Otherwise w_{ij} = 0. **R** is a rotation matrix, **t** is a transla-

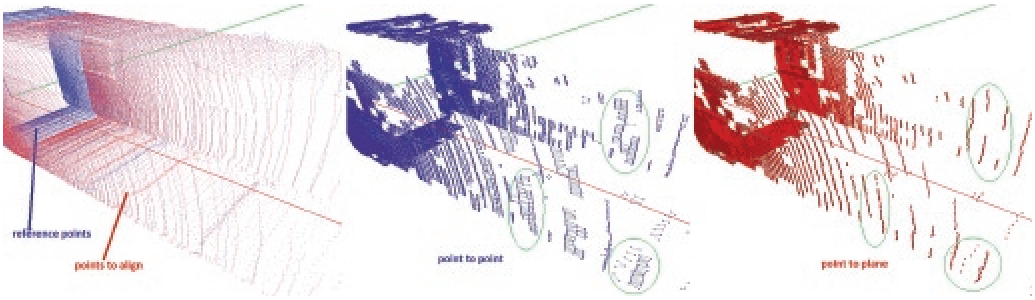

Fig. 1. Comparison between point to point and point to plane methods. In the central image correspond points are connected via line segments. When we are sampling from two different perspectives, we will not in general sample the exact same point. Point to plane method eliminates this problem (green circles)
Rys. 1. Porównanie pomiędzy metodami point to point oraz point to plane. Na środkowym rysunku przedstawiono wyznaczone pary punktów połączone odcinkami. Podczas gdy dokonujemy pomiaru z dwóch różnych perspektyw, nie jest możliwe trafienie tego samego punktu. Metoda point to plane eliminuje ten problem (zielone okręgi)

tion matrix. $\mathbf{m}_i$ and $\mathbf{d}_i$ corresponds to the i-th point from model set M and D respectively. The alignment of M and D data sets for point to plane ICP is solved by minimization of the following cost function:

$$E = (\mathbf{R}, \mathbf{t}) = \sum_{i=1}^{N_{m^p}} \sum_{j=1}^{N_d} w_{ij} \left\| \mathbf{m}^p{}_i - (\mathbf{R}\mathbf{d}_j + \mathbf{t}) \right\|^2 \tag{2}$$

where $\mathbf{m}^p_i$ corresponds to projected point from data set D onto approximation plane of data set M. We can assume that INDOOR dataset is locally planar. Furthermore, since we are sampling from two different perspectives, we will not in general sample the exact same point. For this reason in theory point to plane method is more accurate than point to point (see *Figure 1*).

hybridICP

hybridICP algorithm combines point to point and point to plane methods into one algorithm. Equations 1 and 2 are combined into 3rd equation:

$$E = (\mathbf{R}, \mathbf{t}) = \sum_{i=1}^{N_{m^c}} \sum_{j=1}^{N_d} w_{ij} \left\| \mathbf{m}^c{}_i - (\mathbf{R}\mathbf{d}_j + \mathbf{t}) \right\|^2 \tag{3}$$

where m^c_i denotes found correspond pair-points for points from data set D ("point to plane" point or "point to point" if local approximation plane does not exist). The parallel implementation using NVIDIA CUDA technology is shown on listing 1. Parallel implementation is based on regular grid decomposition of 3D space XYZ (x<-1,1>, y<-1,1>, z<-1,1>) into 256 × 256 × 256 buckets, where single bucket corresponds to cubic subspace with dimensions: 2/256 × 2/256 × 2/256.

listing 1 – hybridICP

copy data from host(M_{host}, D_{host}) to device(M_{device}, D_{device})
in parallel compute M_{planes} for M_{device} points
choose 1 $M_{planeofbucket}$ for each bucket
for iter = 1 **to** 100 **do**
  in parallel
    for i = 1 **to** N_d **do**
      if local approximation does not exist
          find closest point from data set M_{device}
        else
          find projection point
        end if
    end for
    calculate (**R**,**t**) to minimize equation 3
end for
copy D_{device} to D_{host}

Experiments

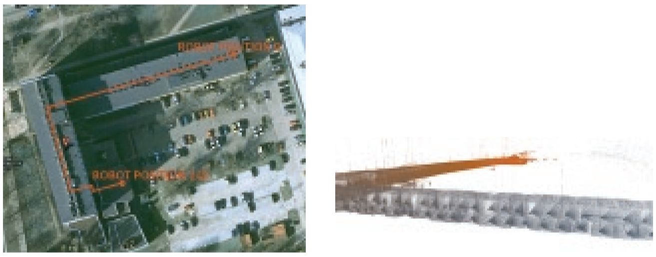

Fig. 2. Left- robot path during INDOOR 3D data acquisition, right – raw data
Rys. 2. Lewy- ścierzka robota podczas akwizycji danych w środowisku INDOOR, prawy – surowe dane

Experiments where performed in INDOOR environment shown on *Fig. 2*, where robot was acquiring observations in stop-scan fashion in one meter step. The goal was to align iteratively all scans, therefore the odometry error was deceased. INDOOR data set is composed of 162 scans of 361 × 498 3D data points. Raw data is show on *Fig. 2* – right. The computation is performed using NVIDIA GF 580 GTX GPGPU. The comparison between the robot trajectory based on combined odometry with gyroscope correction system and GPGPU based classic ICP and hybridICP is shown on *Fig. 9*. The error E(R,t) (see eq. 3) for each robot position in function of ICP algorithm iterations is shown on *Fig. 3.* The error E(R,t) is decreasing monotonically during performed ICP iterations showing its convergence to local minimum. The comparison between classic ICP and hybridICP is shown on *Fig. 4*-left, where positive values of $\text{error}_{\text{classicICP}}$-$\text{error}_{\text{hybridICP}}$ correspond to the situation when hybridICP has lower error compared to classic ICP. Theoretically this situation should appear for all computations, but in real application there are several situations where point to plane method is less accurate than point to point, it is shown on *Fig.* 5 (stairs), and *Fig. 6* (corner). We observed that stairs and corners are difficult to approximate, therefore it can affect hybridICP accuracy. *Figure 4*-right is showing an amount of points projected onto locally approximated planes in percentage. An example of data set containing 7% of points that where able to be projected during hybridICP computation is show on *Fig. 7*, and 30% on *Fig. 8*. The total time of GPGPU hybridICP computation (average 600 milliseconds for 50 iterations) is very optimistic and guarantee on-line execution.

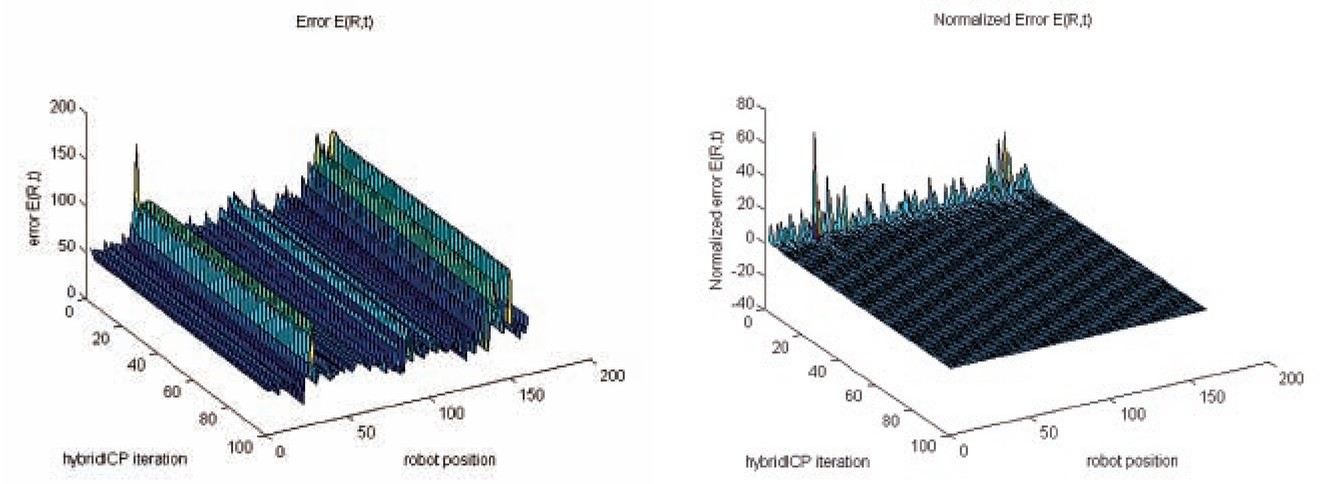

Fig. 3. The error E (R, t) (see eq. 3) for each robot position in function of hybridICP algorithm iterations
Rys. 3. Błąd E (R, t) (równanie 3) dla każdej pozycji robota w funkcji liczby iteracji algorytmu hybridICP

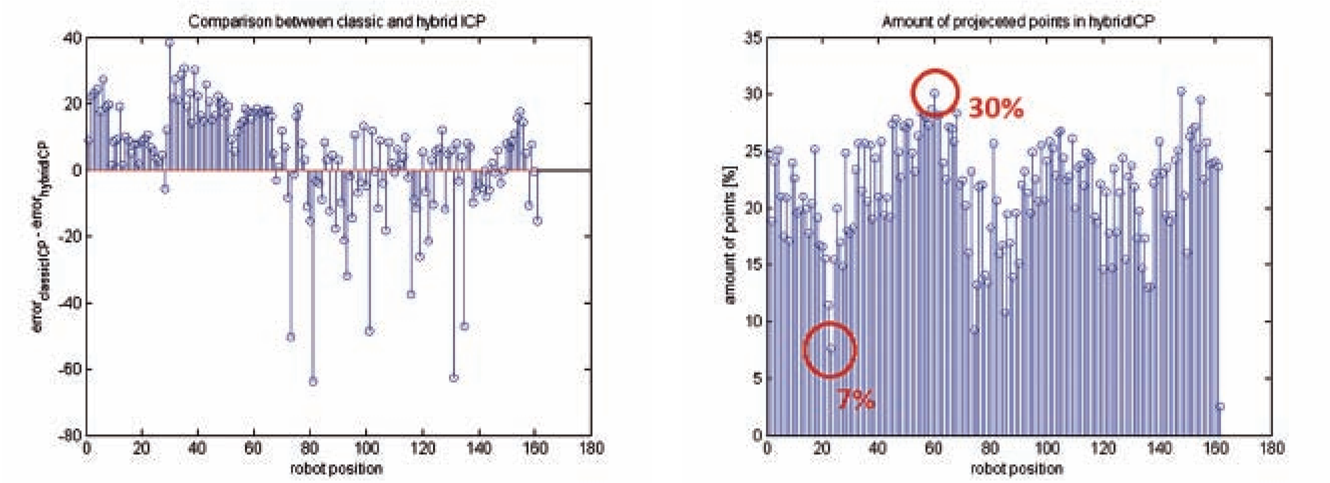

Fig. 4. Left-comparison of classic ICP and hybridICP accuracy. Positive value corresponds to higher accuracy of hybridICP over classic ICP. Right-an amount of points projected onto locally approximated planes in percentage
Rys. 4. Lewy-porównanie dokładności algorytmów classic ICP z hybridICP na bazie różnicy błędu. Dodatnia wartość oznacza przewagę algorytmu hybridICP nad algorytmem klasycznym. Prawy – liczba punktów rzutowanych na lokalnie aproksymowane płaszczyzny wyrażona w procentach

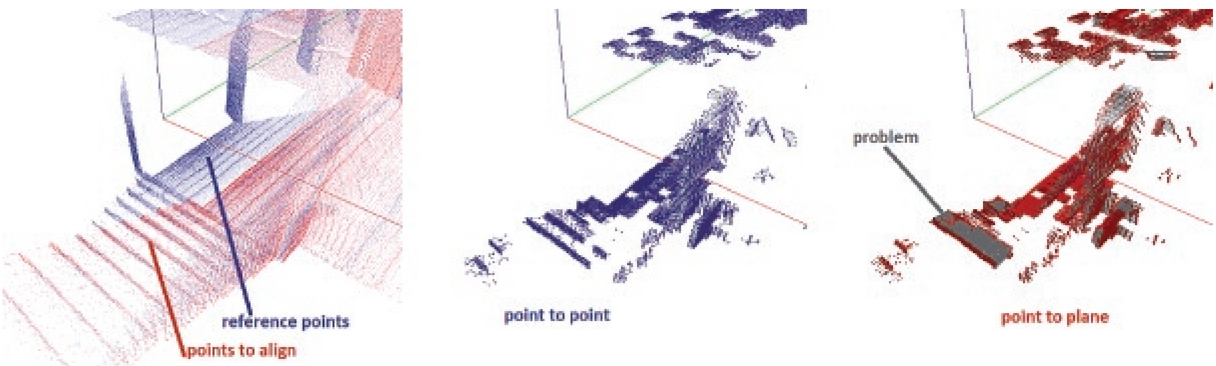

Fig. 5. Problem of point to plane ICP in data containing stairs
Rys. 5. Problem algorytmu „point to plane" wynikający z danych zawierających schody

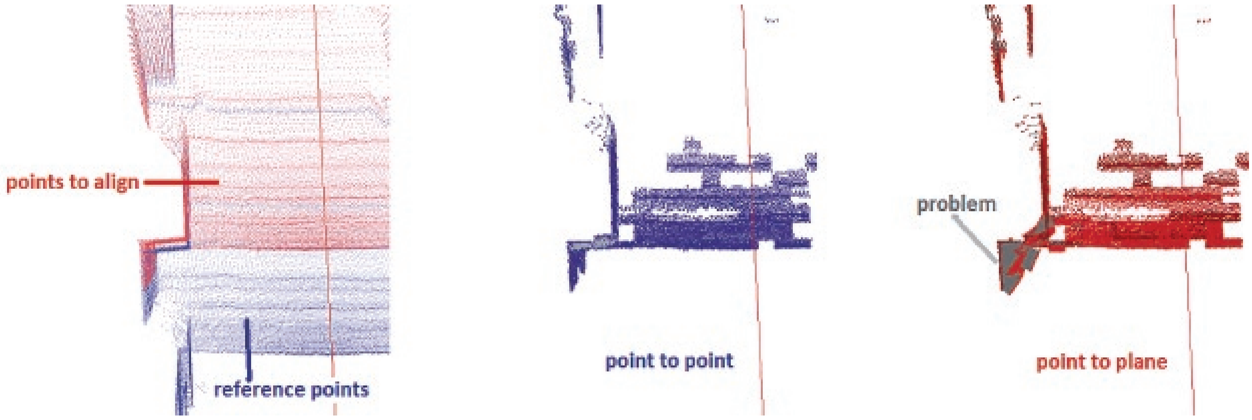

Fig. 6. Problem of point to plane ICP in data containing corner
Rys. 6. Problem algorytmu „point to plane” wynikający z danych zawierających narożnik ściany

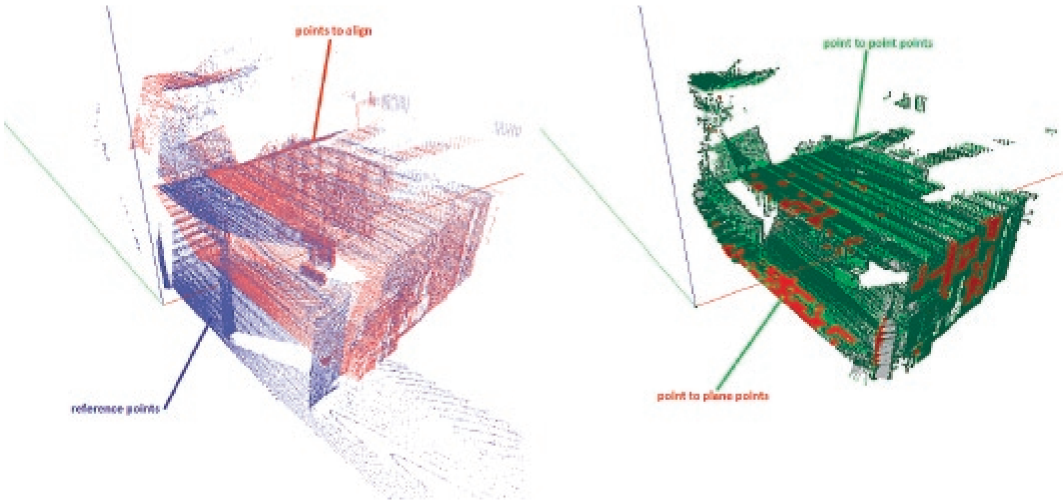

Fig. 7. An example of data set containing 7% of points that where able to be projected during hybridICP computation
Rys. 7. Przykład danych zawierających 7% punktów mogących być zrzutowancych w algorytmie hybridICP

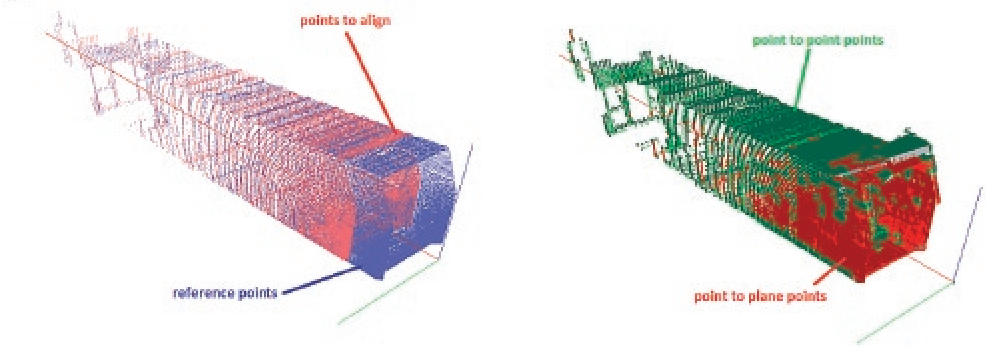

Fig. 8. An example of data set containing 30% of points that where able to be projected during hybridICP computation
Rys. 8. Przykład danych zawierających 30% punktów mogących być zrzutowancych w algorytmie hybridICP

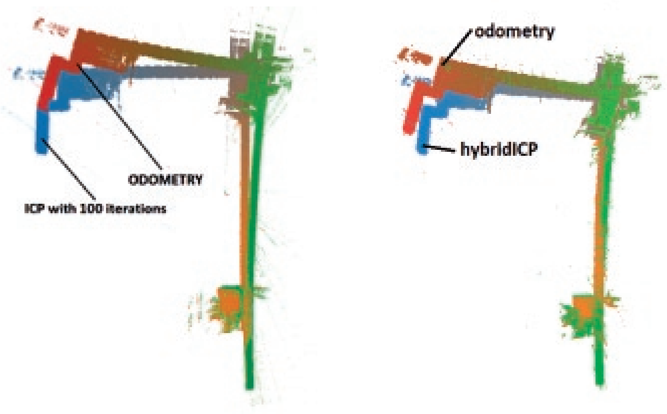

Fig. 9. The comparison between the robot trajectory based on combined odometry with gyroscope correction system and GP-GPU based classic ICP and hybridICP
Rys. 9. Porównanie trajektorii robota wyznaczonej a podstawie odometrii z żyroskopowym systemem korekcji oraz klasycznym algorytmem ICP oraz hybridICP

Conclusion

In the paper new implementation of hybridICP data registration algorithm based on composition of classical approaches point to point and point to plane is shown. The improvement is based on parallel computation applied mainly for k-nearest neighbor search and parallel projection of points. Also empirical evaluation based on data set delivered by mobile robot equipped with commercial available 3D laser measurement system working in INDOOR environment is shown. Based on empirical evaluation we can stated that hybridICP algorithm guarantee better accuracy than classic ICP in most cases except situations where data contains complex shapes such as stairs or corners where problem with approximation easily appear. Future work will be elimination such problems by research concerning accurate approximation techniques that can be implemented using GPGPU. In this paper we demonstrated data registration technique that can be used On-Line during robot motion, therefore is has high potency of integration with real robotics systems.

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