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Alternative Methods for Estimating Plane Parameters Based on a Point Cloud

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Non-contact measurement techniques carried out using triangulation optical sensors are increasingly popular in measurements with the use of industrial robots directly on production lines. The result of such measurements is often a cloud of measurement points that is characterized by considerable measuring noise, presence of a number of points that differ from the reference model, and excessive errors that must be eliminated from the analysis. To obtain vector information points contained in the cloud that describe reference models, the data obtained during a measurement should be subjected to appropriate processing operations. The present paperwork presents an analysis of suitability of methods known as RANdom Sample Consensus (RANSAC), Monte Carlo Method (MCM), and Particle Swarm Optimization (PSO) for the extraction of the reference model. The effectiveness of the tested methods is illustrated by examples of measurement of the height of an object and the angle of a plane, which were made on the basis of experiments carried out at workshop conditions.

Keywords: Robotic inspection, plane detection, Particle Swarm Optimization, RANSAC, Monte Carlo Method.

1. INTRODUCTION

There has been continuous development of flexible means of production in recent years, and it included industrial robots and fast and accurate laser displacement sensors that allow for non-contact measurement techniques. This encourages engineers to design fully automated quality control operations carried out directly at a production workshop. Benefits that can be achieved here include full automation of measurements that are often carried out in an environment that is hostile to man, improvement of objectivity of measurements by eliminating the human error, holding of information about the quality of produced machine parts in the early stage of the manufacturing process, and fuller use of the potential of industrial robots installed on production lines. The fact that a measurement made using a laser beam is a non-contact measurement makes it possible to avoid a collision between the measuring sensor and an object, measurement of hard-to-reach surfaces, often dirty or hot. Results of measurements of geometrical dimensions achieved with this method are not as reliable as in the case of measurements made in measurement laboratories. To reduce these differences simulation methods to assess measurement strategies and determine components of uncertainty of measurements carried out in accordance with a chosen strategy need to be developed.

The measurement result is always different from the unknowable actual value of a measured quantity. This is mainly due to the imperfection of measuring instruments and measurement techniques and the conditions of making measurements. Therefore, the result of a measurement without providing its accuracy is not that meaningful. The measure of accuracy of a measurement is the uncertainty of measurement that characterizes the dispersion of values that can be reasonably attributed to the measurand.

The actual value of the measurand is unknowable, so the measurement error is unknowable as well. Measurement errors can be grouped into three categories: random errors, systematic errors, and excessive errors. A complete measuring procedure should provide the possibility of classification of error into one of these categories. When identifying an excessive error, the measurement must be rejected and repeated. In case of systematic errors their value must be assessed and/or a method of compensation must be developed. Random errors are errors caused by an accidental effect of a large number of intangible interfering factors the total impact of which changes with the next measurement. Thus, measurement uncertainty should primarily concern the characteristics of random errors. The uncertainty of measurement based on which a product is qualified as one that complies with requirements must be in a proper relation to the tolerance of a controlled quantity. The uncertainty budget of measurement normally contains several components of measurement uncertainty. Determining which components of uncertainty are important in the context of tolerance of measurement is one of the main tasks of a technician that compiles measurement results.

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The use of techniques of statistical analysis is becoming a standard in the field of measurement uncertainty estimation [1], [2], [3]. The Monte Carlo simulation method (MCM) was developed in the 1940's by S. Ulamowski. MCM is used for mathematical modelling of processes that are far too complex to be able to predict their results using an analytical approach. Sampling according to the selected distribution of values characterizing the process plays an important role in MCM. After collecting a sufficiently large amount of such information its characteristics can be compared with the observed experimental results, confirming or denying the validity of assumptions made in the entire procedure. The accuracy of a result obtained by this method depends on the number of checks and the quality of the random number generator.

Currently, there are more effective methods to browse through decision-making space, often multi-dimensional, than MCM, which are also random in nature. These include a group of methods based on a paradigm of a cluster of particles moving in n-dimensional space. The direction and rate of movement of individual particles is partly determined by their inertia, the best location remembered, and the location of the best located particles in the entire cluster. Applying these simple rules in simulation models, it is possible to speed up the search for a satisfactory solution and/or improve their quality.

The efficiency of determining the estimated model parameters using random methods depends mainly on the number of dimensions of decision-making space and on the possibility to limit the search scope in a given dimension. As shown in paper [4], the possibility of using discrete decision-making space accelerates the time to generate results and improve its quality.

The presented paper concerns a study on measurement possibilities carried out by means of an LK-H152 triangulation sensor with an LK-G5001P controller mounted on a flange of a 6-axis industrial robot with anthropomorphic kinematics (Fig.1.). Results of coordinate measurements, which we deal with in the course of measurement by laser sensor, are subject to errors of designation of position and orientation of the reference system and errors of designation of position and orientation of measured surface relative to the reference system. To make a correct determination of a measuring instrument coordinate system (TCP), a laser beam detector dedicated to this task was developed.

This article presents results of research on measurements carried out in a direction that is parallel to the laser beam, bypassing the problem of detecting the edge of an object in directions that are perpendicular to the laser beam. A measurement made in a direction that is parallel to the beam can identify planes, for example. Therefore, measurements of height, parallelism of planes, angle between planes and plane surface flatness deviations are possible. Such measurements, like any other measurement, are subject to a degree of uncertainty. In this paper the focus is on an important component of uncertainty which is the uncertainty of the calculation method used to determine the plane model. Another important component of uncertainty in this type of measurements is the laser sensor reading error that is related to the relaxation time of the measurement system. This error for this position was analyzed [5]. Therefore, the adopted period of relaxation in the conducted experiments was constant at 1 second. Errors resulting from the robot's failure to achieve the programmed position were compensated for by a direct reading of the actual final position of the robot arm to which the measuring sensor was attached. Such a behavior is acceptable in cases where we are sure that the axes of the robot are accurately calibrated. Due to small values, the reading error of the actual position by the robot's measuring systems was considered measurement noise compensated by the increased number of measurement points.

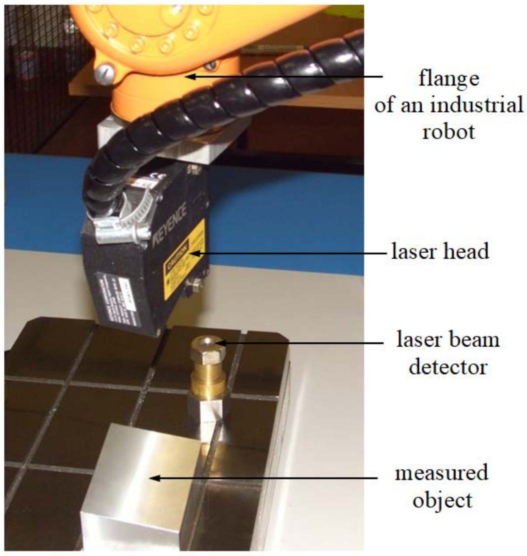


Fig.1. General view of the test bench.

Determination of a correct model for the measurement of geometrical values may give rise to various difficulties. Estimation of uncertainty of coordinate measurements is a very complex task due to the diversity of measured characteristics, strategies, and measurement methods. Therefore, the analytical estimation of uncertainty of coordinate measurements should be supported by specialist software [6].

2. ROUGH DETERMINATION OF PLANE USING RANSAC

RANSAC algorithm [7], [8] is an iterative method used to estimate sought parameters of the mathematical model of object based on a redundant set of data points, forming a cloud around the determined area. This collection, in addition to the points located very close to the area, also contains many points burdened with measurement noise; there may also appear excessive errors. The algorithm essentially comprises two repeated iterative phases: initialization and test. Initialization phase consists of random selection of a minimum set of points needed for an unequivocal determination of the estimated parameters of model geometry and to determine the parameters of this model. The identified model is a hypothesis, which is tested in the next phase - test. During the test, the distance of remaining points of data from the created model is calculated. In the original formulation of the algorithm by Fischler and Bolles [7], criterion for assessing the quality of the model is the size of a set of consensus *card(CS)*. *CS* consists of points, the distance of which from the model is less than the threshold δ. The selection of an appropriate δ value is essential for the stability of the RANSAC algorithm and has an essential impact on the quality of separated surfaces, in addition to the number of iterations. Fig.2. illustrates how the size of CS changes depending on δ threshold and selected arbitrary number of *iter* iterations of the RANSAC algorithm. It can be observed that for small *iter* the graph is monotonic, and the obtained *card(CS)* values are understated, especially for small δ, which proves the possibility of missing the best solutions. The problem of the number of iterations is critical in cases of application of the RANSAC method for the extraction of planes on the basis of point cloud with a significant number, order of several hundred thousand and more. Execution time for calculations can be in these cases fatal. In this work's experiments the sum of points does not exceed 1000, so the calculation time was negligible compared to the time of measurement.

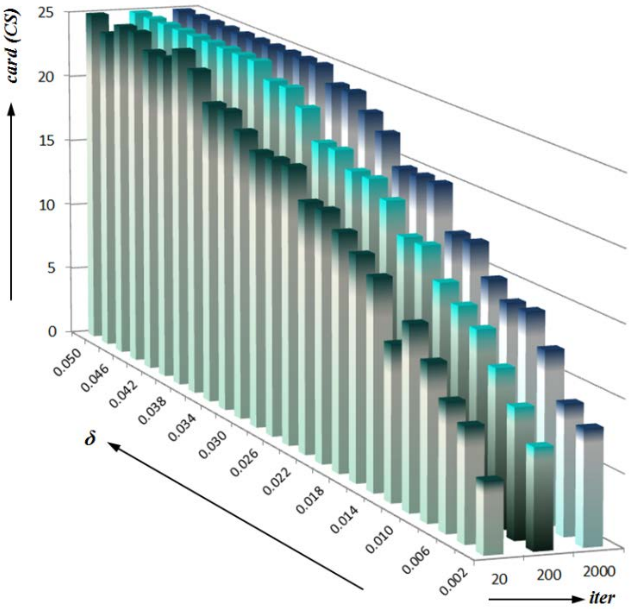


Fig.2. Evolution of *card(CS)* depending on δ and the number of *iter* iterations of the RANSAC algorithm.

According to [9], the value of δ can be determined on the assumption that all measuring points are subject to errors with normal distribution. Central limit theorem states that with more random variables influencing the performance of measurement, the distribution is close to normal. We are dealing with such a situation during measurements with laser sensor installed on the robot flange, carried out under the conditions of the production workshop.

For a given normal distribution with a known standard deviation σ the δ parameter allows to determine the probability of given point *p* belonging to the *CS* according to the dependence:

$$p = \frac{1}{2}\left(1 - erf\left(\frac{\delta}{\sigma\sqrt{2}}\right)\right) \tag{1}$$

where:

erf – error function,

σ – standard deviation.

Modifications proposed in [9] reduce the processing time, allowing dynamic selection of an appropriate number of iterations, successively amended after each appointment of better model. The number of additional *iter* iterations is determined according to (2) and is:

$$iter = \frac{\log(1-P)}{log\left(1-\frac{(card(CS))^3}{N(N-1)(N-2)}\right)} \tag{2}$$

where:

P – probability of identifying the correct plane,

card(CS) – the size of *CS* set,

N – number of all measuring points of data set.

Fig.3. illustrates how *iter* parameter changes for small *N*=const=25 and δ=const=0.03. Fig.4. illustrates how to form the output variables of *card(CS), NCS* - the number of iterations required to achieve a given *CS*, *Add* - the number of additional iterations, during which the result and *Total* were not improved - the total number of iterations. These results were obtained for *P*=0.999 and *N*=25.

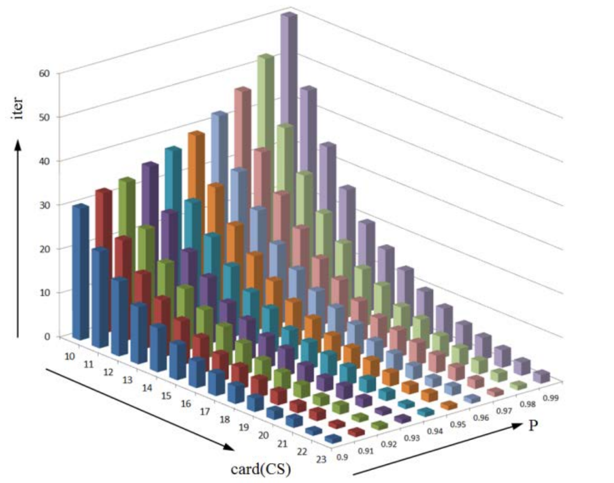


Fig.3. The evolution of number of iterations according to the size of the current set of CS consensus and the probability *P* of identification of the best model for the number of measurement points *N*=25 i δ=0.03 mm.

As is apparent from Fig.4., the necessary number of iterations does not exceed 250 in any trial as compared to the number of permutations of three-element sample with 25-element set of 13800 and it is the result justifying the use of the proposed approach. RANSAC method, as proposed by its creators, does not guarantee that the resulting solution is optimal for the threshold δ. Therefore, there are works in which the authors propose to consider additional criteria, improving the quality of solution. In reference [10], the following rule to change the model was proposed:

$$\left.\begin{array}{r} card(CS) > \max\limits_{card}(CS)\; or \\ card(CS) = \max\limits_{card}(CS)\; and\; \sigma < \min\_\sigma \end{array}\right\} \qquad (3)$$

where:
$\max_{card}(CS)$ – maximum reached cardinality of *CS*,
min_σ – minimum value of the standard deviation for the models for which $card(CS) = \max_{card}(CS)$.

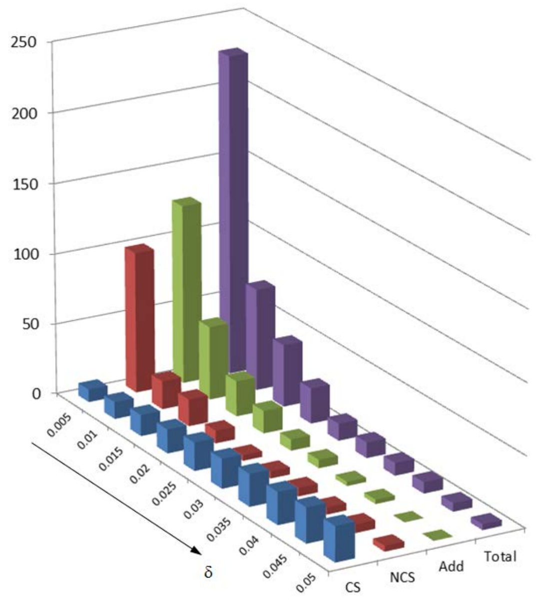


Fig.4. Development of cardinality of *CS* set and the number of iterations required to achieve these results depending on pre-set threshold δ.

RANSAC method, although effective in the case of very large sets of points cannot be included in the precise methods for the measurement of small area and with a small number of measuring points. The method assumes that the three points are randomly selected to a designated plane, while each point is defined with unknowable error. Therefore, the determined plane can only be regarded as an approximation of the optimal solution. Nevertheless, the RANSAC method can significantly reduce the search area, and thus accelerate the effect of more accurate methods.

3. ESTIMATION OF POSITION AND ORIENTATION OF THE PLANE BY RANDOM METHODS

The search for solution through random search of decision space of estimated model parameter is a recognized and even a preferred method of finding solutions [1], [3]. To reduce the likelihood of omission of the optimal solution, to improve the quality of solutions and at the same time to reduce the computation time it is very beneficial to limit the size of search area of conditions. In case of estimating position and orientation of plane, the RANSAC method can be used.

Let the estimated plane associated with the coordinate system XYZ_E in reference coordinate system XYZ_R (Fig.5.) determine displacement vector of coordinate origin $\overrightarrow{RE}=[x_R, y_R, z_R]^T$ and differential vector of orientation $\overrightarrow{RE}=[x_R, y_R, z_R]^T$. Vector $\overrightarrow{R"E'}$ can be clearly determined by giving its *r* and the angle of rotation γ around Z'_R axis. This allows to determine the components of the X and Y axis. The third component in the Z-axis results from the assumption that the vector has unit length. Decisive area in the above premise will be five-dimensional, and its parameters are x_R, y_R, z_R, r, γ. Origin of the unit normal vector of the estimated plane is inside a sphere with a center at point R and radius ρ, while its end is on the area of sphere segment embedded at point E, with unit radius and angle 2ε. Parameters ρ and ε define in this case the size of decisive area in search for the best suited plane. Number of degrees of freedom of determined model can easily be limited to three, after the adoption of easy to accept assumptions: determined plane is not parallel to Z_R axis, point *E* lies on Z_R axis and component Z of vector $\overrightarrow{RE}$ has a direction agreeing with the Z_R axis. Then the decisive area has only three dimensions z_R, r, γ, which significantly speeds up the process of estimating the correct plane. The position of decisive area in the latter case changes dynamically, as component Z_r is set to a range $\pm dZ$ with respect to the best currently achieved solution.

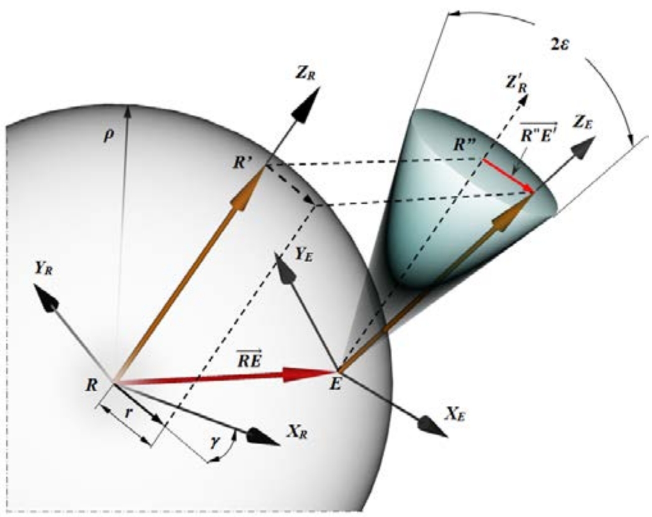


Fig.5. Reciprocal linking of geometric size in estimation position and orientation of the plane.

MCM method applied to solve the task of estimating the best suited plane is based on random generation of model of the plane, and then verification of the model fitting to the measuring point cloud. Each point in the above defined five-dimensional decisive area represents one plane. Repeating the cycle of generation and test several times, we were able to reach a satisfactory solution. Match criterion of generated plane to the point cloud is usually the minimum sum of squared distances of measurement points of the estimated plane. MCM is therefore simple to implement, even directly in the control system of an industrial robot. The only requirement is access to the proper quality of random number generator.

A more advanced, but also random method of searching the state space is first proposed by the Kennedy and Eberhart method of swarm of particles [11]. Basis of optimization methods derives from the natural behavior of living individuals, living and moving in large clusters as fish, birds, bees, etc. Each individual (particle) is determined to achieve the best position in the swarm, guaranteeing it survival, access to food and/or reproduction. Hence, the movement vector of particle (Fig.6.) to a new position $\overrightarrow{P_aP_n}$ is the result of three components: inertia component of particle $\overrightarrow{P_aP_1}$ determined as part of the motion vector in the previous iteration cycle, a component resulting from the best position of particle in the swarm $\overrightarrow{P_1P_2}$, and the component resulting from the best position so far memorized by the particle $\overrightarrow{P_2P_n}$.

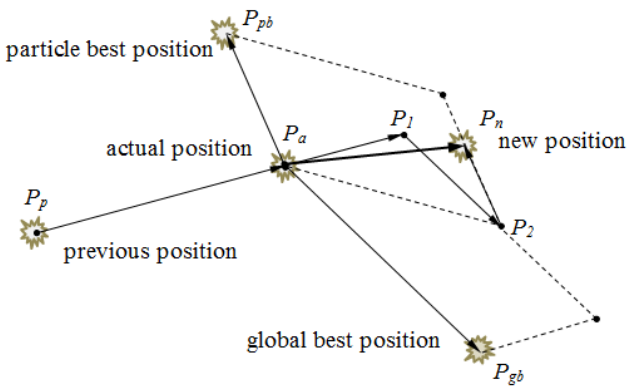


Fig.6. Determination of the new position of particle in the method of PSO.

Movement of the particle in subsequent movements described by the equation:

$$\left.\begin{aligned}\overrightarrow{P_aP_n} &= \overrightarrow{P_aP_1} + \overrightarrow{P_1P_2} + \overrightarrow{P_2P_n}\\ \overrightarrow{P_aP_1} &= w_1R_1\overrightarrow{P_pP_a}\\ \overrightarrow{P_1P_2} &= w_2R_2\overrightarrow{P_aP_{gb}}\\ \overrightarrow{P_2P_n} &= w_3R_3\overrightarrow{P_aP_{pb}}\end{aligned}\right\} \tag{4}$$

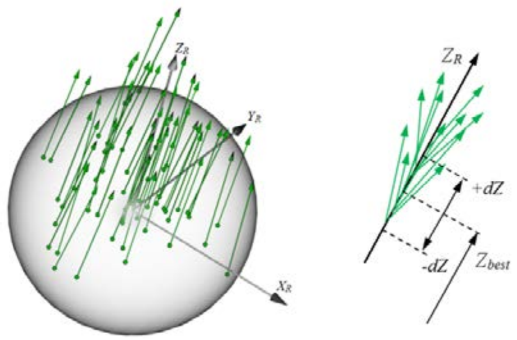
where:

w_1, w_2, w_3: weight of individual components,

R_1, R_2, R_3: random numbers in the range [0,1] of the normal distribution.

Many researchers are trying to introduce the modifications to the basic PSO algorithm [4], [12], [13]. They focus mainly on the dynamic control of weights of individual components. Positive results can be achieved by setting initial low weight w_2, which ensures uniform penetration throughout the decisive area through swarm, in the first phase of the algorithm. In turn, determination of high level of w_2 in the final phase causes the particles to penetrate the closed area exactly at the best solution, which allows further improvement of the solution. It is also proposed to introduce a global factor of speed of the particle, allowing reducing the value of position correction in the final phase of the algorithm. Authors' own experience shows that properly chosen and dynamically adjusted speed of particles has a decisive influence on the efficiency of PSO algorithm. Another line of modifications concerns the resignation of globally best representative of the population in favor of locally best representatives within a certain environment. Further modifications can affect the introduction of braking mechanism of the particles in the event of leaving the acceptable area. Alternatively, the solution is killing the particle after crossing the allowable area and generating in its place a new particle. This latter approach brings the PSO algorithm closer to the genetic algorithm.

PSO method in the context of the search for the best suited plane requires in its first chase of swarm initialization generating a set of unit vectors, embedded inside a sphere with center at the reference radius ρ (Fig.7.a)), or embedded in a section of Z_r axis (Fig.7.b)). During this phase the best-defined particle of pre-generated random collection is found. Drawn position of the particle is initially recognized as the best position of the particle. This phase does not differ from the MCM method. In the next iteration steps, each particle changes its position according to (3). The algorithm on-line modifies the best position of the particle and particle with globally best position in the whole swarm.



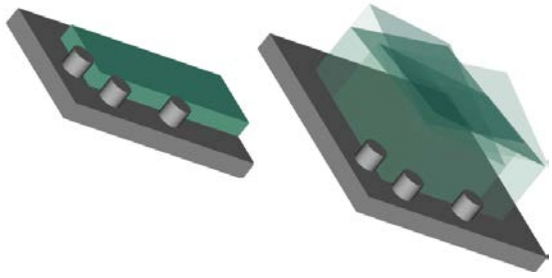
a) generated inside the sphere. b) generated on a section of Z axis.

Fig.7. Swarm of unit vectors.

4. RESULT OF CONDUCTED TESTS

The object of the study were two basic objects in the form of master plate (Fig.8.a)) and a rectangular body in which the upper area was beveled with respect to the base at an angle of about 10° (Fig.8.b)). For the master plate height research was conducted, whereas the second object was set in four different positions (0°, 90°, 180°, and 270°), in each case in order to determine the angle between the base area and the top area.

The first stage of tests compared the speed of the method and sensitivity of the results achieved on the size of decisive area, characterized by parameters dZ and ε. The test results allow to conclude that MCM (Fig.9.) requires a very large number of iterations to achieve satisfactory results. In the present test, the criterion was to achieve a standard deviation of less than 0.019. MCM is also very sensitive to increase in the decisive area. Doubling the dimensions of decisive area increased the computation time 10 times. In case of the PSO method (Fig.10.), the number of iterations to achieve a satisfactory outcome fluctuated at the level of less than 5000, without showing visible dependence on dimensions of the decisive area. Given the size of the population of particle swarm (50), the calculation time for obtaining criterion was 4 times less than in the case of MCM.



a) Master plate. b) Cuboid with a beveled wall.

Fig.8. Measured object.

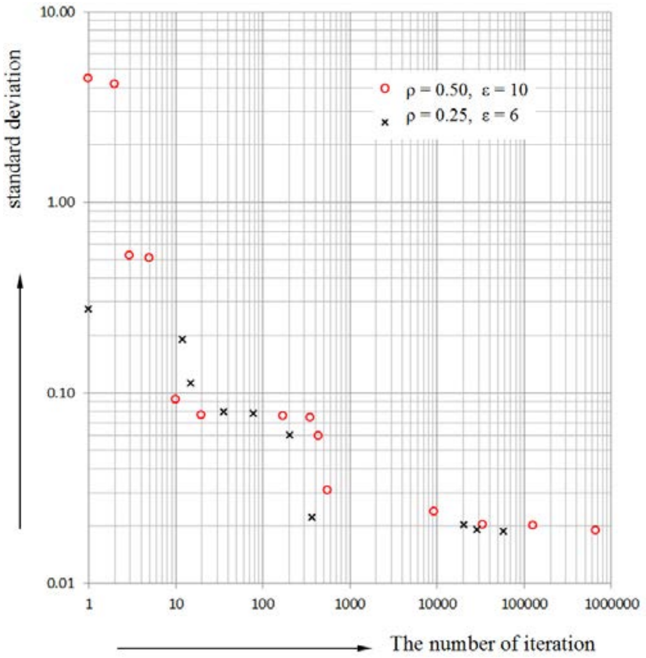


Fig.9. Examples of two courses of the RANSAC+MCM algorithm.

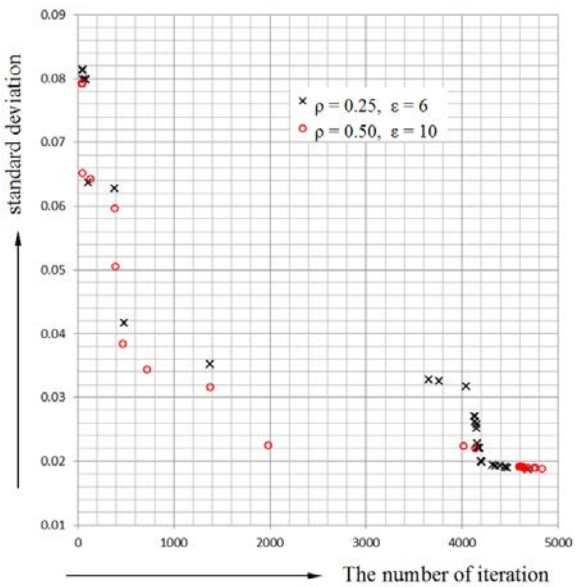


Fig.10. Examples of two courses of the RANSAC+PSO algorithm.

For the determination of uncertainty components arising solely from the computational method a series of tests on the same measurement data was carried out, each repeated 25 times. The results of computation of plane position in the Z axis and the angle of the plane in relation to the reference plane were shown in Table 1. Differences in the reproducibility of each method are best illustrated in Fig.11. and Fig.12., representing graphs of probability density, assuming that the distributions are normal.

Table 1. Test results illustrating reproducibility of calculation methods.

Method	Z position, mm		Angle, …°	
	average	Std. Dev.	average	Std. Dev.
RANSAC	9.853	0.0071	10.289	0.0131
PSO	9.843	0.0036	10.293	0.0070
RANSAC+MCM	9.836	0.0047	10.268	0.0072
RANSAC+PSO	9.849	0.0018	10.286	0.0028

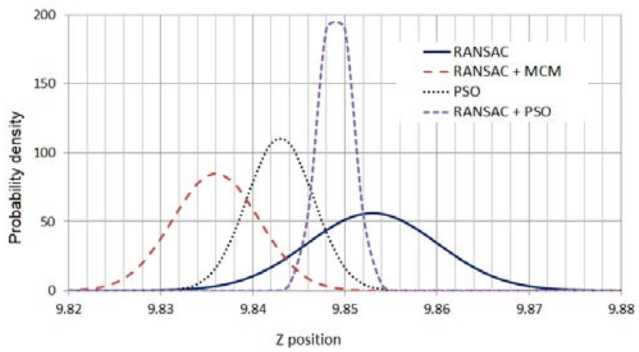


Fig.11. Comparison of repeatability of four methods of calculation when determining the position of the plane in Z axis.

Table 2. shows calculation results of the angle of inclination of the top plane of measured object (Fig.8.b)) to the base plane in four different angular settings relative to the base. The calculation was carried out in four methods described above.

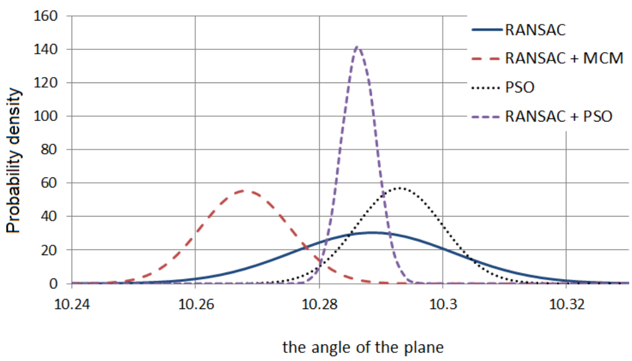


Fig.12. Comparison of repeatability of four methods of calculation when determining the angle of the plane in relation to the reference plane.

Table 2. Results of measurements of the angle of inclination of inclined area.

Method	position	number of tests	min ...°	max ...°	average ...°	std. dev. ...°
RANSAC	0°	25	9.994	10.115	10.039	0.034
	90°	25	10.168	10.255	10.217	0.023
	180°	25	10.234	10.315	10.286	0.025
	270°	25	10.179	10.266	10.218	0.023
	All	100	9.994	10.315	10.190	0.096
RANSAC + MCM	0°	25	9.991	10.126	10.039	0.040
	90°	25	10.212	10.265	10.239	0.016
	180°	25	10.214	10.336	10.286	0.037
	270°	25	10.201	10.256	10.225	0.015
	All	100	9.991	10.336	10.197	0.099
PSO	0°	25	9.968	10.032	9.994	0.017
	90°	25	10.141	10.283	10.223	0.045
	180°	25	10.280	10.321	10.303	0.010
	270°	25	10.160	10.240	10.197	0.020
	All	100	9.968	10.321	10.179	0.095
RANSAC + PSO	0°	25	9.991	10.031	10.007	0.010
	90°	25	10.308	10.333	10.320	0.007
	180°	25	10.263	10.289	10.280	0.007
	270°	25	10.128	10.158	10.139	0.009
	All	100	9.991	10.333	10.187	0.124

The best is the RANSAC + PSO method. The standard deviation score for each of the four different settings does not exceed in this case 0.01°. At the same time this RANSAC + PSO method is best illustrated by the fact (Fig.12.) that in the case of measuring the same surface in various settings of the object one should expect a certain discrepancy of results. In order to obtain the results of the measurements of normal vector components of the plane subject to a low rate of uncertainty, you should take in the same position of the object and previously eliminate systematic error by taking into account the results of pattern measurement of the angle, carried out in the same position and in the same workshop conditions.

Table 3. shows the results of measurement of height of the plate, by designating the position of base plane and the upper plane. Measurements of the height of the plate with micrometer device showed differences in the height of the plate in the area 8.998÷9.005. Presented results relate to the corners of the plate with the greatest height. Results of conducted tests of measurement of height of the object with laser sensor also prefer the RANSAC + PSO method, for which the standard deviation is less than half than for the RANSAC method alone.

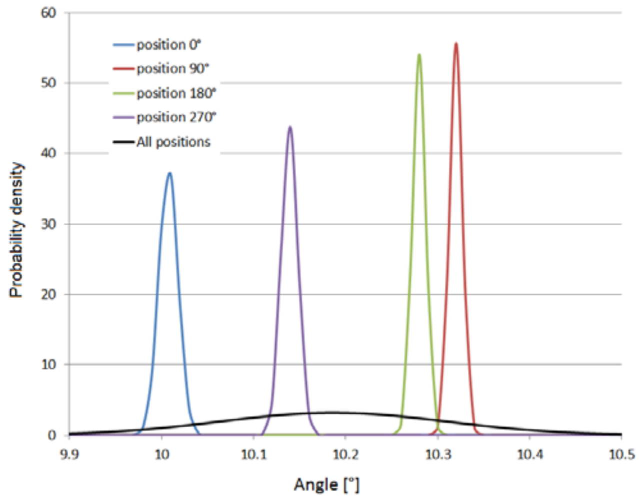


Fig.13. Dispersion of the results of the measurement of angle of inclination of plane using RANSAC+PSO.

Table 3. Results of measurements of the height of master plate.

Method	number of tests	Min [mm]	Max [mm]	Average [mm]	std. dev.
RANSAC	25	8.981	9.037	9.012	0.013
RANSAC+MCM	25	8.982	9.029	9.006	0.011
PSO	25	8.996	9.027	9.013	0.008
RANSAC+PSO	25	9.000	9.018	9.014	0.006

5. SUMMARY

The presented paper shows four approaches to estimation of the position and orientation of the plane based on a cloud of scanned points. The RANSAC method, although simple to implement, can only roughly estimate the parameters of the studied plane. However, it allows the removal of excessive errors that may appear in a cloud of scanned measurement points. It also radically reduces the search area, in the next phase of accurate estimation of parameters of the plane. The Monte Carlo method is also easy to implement, but it needs a very large number of iterations to achieve a satisfactory result. The rationale for its use is when we are able to reduce the search area to a very small size and calculation time is not too important. The PSO method is very effective, but has a developed algorithm that also needs to be adjusted by carrying out a series of simulation tests. This requires more experience and competence from the person using this algorithm. A combination of RANSAC with random optimization methods gives the best results both in terms of time to generate results and their quality.

All considered methods in a wide range use random values and statistical functions. Unfortunately, control systems of industrial robots and controllers of optical triangulation sensors do not offer this type of feature as standard. In order to use these methods more widely in practical solutions, manufacturers of industrial robot controllers should equip them with software richer in this regard.

On the basis of the experience it can be said that the current state of the art measuring equipment used and the methodology of calculations, maintaining the proper diligence measurement workshop, can be used for measurements of length tolerated within a range ± 0.05 mm. In case of angular dimensions, the result of the measurement is strongly dependent on the size of the measured area.

It would be a natural continuation of the above research to solve the problem of determining the plane using a mobile robot. Due to the extent of the issue, this may be the subject of another scientific paper.

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