Combining Multiple Shape Matching Techniques with Application to Place Recognition Task

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Abstract. Many methods have been proposed to solve the problem of shape matching, where the task is to determine similarity between given shapes. In this paper, we propose a novel method to combine many shape matching methods using procedural knowledge to increase the precision of the shape matching process in retrieval problems like place recognition task. The idea of our approach is to assign the best matching method to each template shape providing the best classification for this template. The new incoming shape is compared against all templates using their assigned method. The proposed method increases the accuracy of the classification and decreases the time complexity in comparison to generic classifier combination methods.

1 INTRODUCTION

The shape matching problem is studied in various form: (1) the computation problem is to compute the dissimilarity measure between two shapes, (2) decision problem is to decide if two shapes are similar enough to represent the same object and (3) the retrieval problem is to chose the most similar shape from the set of templates. The shape matching is a problem that is solved in context of computer vision, pattern recognition and robotics. Shape matching is one of the key tasks in shape retrieval, object recognition, visual scene understanding or place recognition.

There are many shape matching techniques solving the computation problem and providing dissimilarity measure between patterns. This dissimilarity measure is a function defined on pairs of shapes indicating the degree of resemblance of patterns. A dissimilarity measure should be invariant for the geometrical transformation group and ideally has the properties of metric. The decision problem or retrieval problem is then mostly solved by applying the thresholding or nearest neighbor method respectively making use of the pairwise dissimilarity measure.

In robotics, the place recognition problem is equivalent to the retrieval problem. The task of place recognition is to decide whether a robot is revisiting an already known location or is visiting unknown location using only sensor information. This is crucial for applications like pose initialization and localization using prior maps, closing large loops, simultaneous localization and mapping (SLAM), localization in topological maps or merging maps collected at different time or by multiple robots.

Different types of sensors like cameras, laser range-finders or RGB-D sensors can be used to obtain the information about the places. As the sensor information is limited, two main problems arise: 1) Perceptual aliasing when two different places can be perceived as the same and 2) perceptual variability when the same place provides different sensor readings under different circumstances. The perceptual aliasing can be minimized by using as detailed place description as possible. On the other hand, the detailed description increases the perceptual variability.

Usually the comparison is not performed on raw sensor data, but these data are processed into form of descriptors to decrease memory consumption, increase speed of comparison and robustness. One of the possible representation of the raw sensor data is a shape of the place. In this case, the shape matching techniques is possible to use.

Each shape matching method works for certain class of shapes better and for other type worse. Therefore it is not easy to choose the proper method for given set of templates or set a generally suitable thresholds. In robotics, if the environment consists many subareas of different types (e.g. indoor and outdoor if is considered only the rawest division) it can be impossible to recognize places using only one method. The solution is to use more methods and combine their outputs.

As the retrieval problem or place recognition task can be seen as a multi-class classification problem, it is possible to use the methods for combining classifier, which are widely studied. Classifier combination techniques operate on the outputs of individual classifiers and usually fall into one of two categories. In the first approach the outputs are treated as inputs to a generic classifier, and the combination algorithm is created by training this, sometimes called secondary, classifier. The advantage of using such a generic combinator is that it can learn the combination algorithm and it can automatically account for the strengths and score ranges of the individual classifiers. In the second approach, a function or a rule combines the classifier scores in a predetermined manner. For the review see [1].

In the field of mobile robotics and specifically in place recognition, different classifier combination techniques are used. The voting scheme and nearest neighbor is used in [2]. The AdaBoost is widely used in place recognition and semantic classification of places [3–5]. Another method used in robotics as a generic classifier is Support Vector Machine (SVM) [6].

This paper introduces novel method for combining the methods for retrieval problem based on the knowledge of the template set. As the place recognition methods always compare sensor information representing actual place with data stored in the database of known places, the properties of the reference place from database is known. This information is used to decide which method should be used.

The proposed method finds the best classifier for each known place, which distinguishes this place from all other known places. If a new place is visited, it is compared with all known places. In our method, when the new place is compared with a given known place, the knowledge of corresponding best method is employed. It allows to increase the precision of the classification as this knowledge is utilized. It is called procedural knowledge as defined by [7] because it describes *how to proceed* the comparison involving content specific rules, strategies and actions.

As only one method is used when a new incoming place is compared to stored place, the time complexity is significantly lower than the generic classifier methods combining all the available methods together.

The rest of the paper is organized as follows: next section describes the proposed procedural knowledge-based method combining multiple classifiers. The section 3 describes experimental setup, used datasets and classifiers for combining. The section 4 displays resulting accuracy and time consumption. The paper concludes in section 5.

2 METHOD

The proposed procedural-knowledge based method utilizes specific property of the retrieval problem or place recognition task in robotics. The input to the method is an unknown shape and the set of known template shapes. The template set is known in advance, therefore it is possible to utilize this knowledge to improve performance of the classification.

Let the template set or database $D = \{d_i^j; i = 1...n, j = 1...k\}$ consists of k classes of shapes, where every class is represented by n instances of shapes. Each shape is described by the polygon $d_j^i = \{(x, y) \in \mathbb{R}^2\}$. The notation d_i^j means that the shape d is i^{th} instance of the class j.

The shape matching method, which correctly distinguishes the particular class of shapes from the most other shapes in the template set is used always to measure dissimilarity of this class of shapes. This best method is called procedural knowledge and each class has exactly one shape matching method assigned as a procedural knowledge.

In robotics, the database is called a map, a class is equivalent to the physical location in the environment and instances are the measurements or sensor readings taken in this place and stored in the map. So each place in the environment is represented by n shape descriptors stored in the map D. It is assumed, that each place or class is described by exactly n shapes, without loss of generality.

Let there is set of shape matching methods F, where each method $f \in F$ computes the dissimilarity of two shapes

$$f_i(d_l^x, d_k^y) : D \times D \mapsto \langle 0, 1\rangle\,,$$

where the dissimilarity takes value from an interval $\langle 0, 1\rangle$. The dissimilarity is 0 if the two shapes are identical and takes maximal value 1 if they are totally different.

The shape matching method can provides the dissimilarity measure in range $\langle 0, m_i\rangle$, but all the results can normalized by dividing dissimilarity measure by maximal value m_i. The normalized dissimilarity measure is assumed in the rest of paper without loss of generality.

The classification is then performed using the threshold ϑ_i as

$$c(f_i,(d_k^x,d_l^y),\vartheta_i)=\begin{cases}1 & \text{if } f_i(d_k^x,d_l^y)<\vartheta_i\\ 0 & \text{if } f_i(d_k^x,d_l^y)\geq\vartheta_i\end{cases},$$

where 1 means that d_l^x and d_k^y are from the same class of shapes or represent the same place and classifier declares that $x=y$ and 0 means that they represent different classes or places and $x\neq y$.

The method works in two phases: learning phase and classification phase. In the learning phase, the best classifier is determined for each place in a database. The classification phase takes these best classifiers and compare the novel place with each place in database making use of the procedural knowledge to determine the best classifier.

2.1 Learning phase

The proposed procedural knowledge-based method divides the dataset D into k disjunctive parts D_p such $\bigcup_{p=1}^k D_p=D$ and $\bigcap_{p=1}^k D_p=\emptyset$, where each part $D_p=\{d_i^p : i=1...n\}, p=1,\ldots,k$ contains all shapes of the same class p.

Then, the set of shape pairs $R_p=\{(x,y); x\in D_p, y\in D\}$ are created for each database part D_p, where each element from D_p is paired with each element from the full database D. Any set of pairs $R=R^+\cup R^-$ is a union of positive examples $R^+=\{(x,y): x,y\in D_p\}$, where all shapes to same class and negative examples $R^-=\{(x,y): x\in D_p, y\in D\setminus D_p\}$, where shapes to different classes.

For each class $p=1,\ldots,k$ represented by shapes D_p, a best-matching method f_p^* and corresponding threshold ϑ_p^* is chosen to maximize the F-Score:

$$(f_p^*,\vartheta_p^*)=\arg\max_{f\in F,\vartheta_p^f=<0,1>}\text{FScore}(c(f,R_p,\vartheta_p^f)),$$

where F is a set of all available classificatiors. The F-Score is computed on the pairs R_p. The F-Score represents the quality of the classifier and is computed as a harmonic mean of the precision and the recall using

$$\text{FScore}(c(f,R,\vartheta))=\\(1+\beta^2)\frac{pr(c(f,R,\vartheta))\cdot re(c(f,R,\vartheta))}{(\beta^2\cdot pr(c(f,R,\vartheta)))+re(c(f,R,\vartheta))},\quad(1)$$

where the precision

$$pr(c(f,R,\vartheta))=\frac{\sum_{r\in R^+}c(f,r,\vartheta)}{\sum_{r\in R}c(f,r,\vartheta)}$$

is a fraction of true positive hits out of all instances classified as true (true positive and false positive hits) and the recall (or true positive rate)

$$re(c(,f,R,\vartheta))=\frac{\sum_{r\in R^+}c(f,r,\vartheta)}{|R^+|}$$

is a fraction of true positive hits of a classifier out of all positive cases in a dataset with a given threshold ϑ_i. As there is no preference for precision or recall, we set $\beta = 1$. The perfect classifier has the FScore = 1. The FScore = 0 means that classifier classifies all the positive example wrongly.

We use the F-Score quality measure because the numbers of positive and negative examples are unbalanced. As the number of the negative examples are always significantly higher due to one-to-rest training set, the F-Score provides more relevant results than the widely used accuracy measure.

2.2 Classification phase

The classification phase is very easy. Let there is a unknown shape x. This shape can be acquired, when the robot visit a novel place and processes the sensor data to acquire the shape x describing this place. The aim of the classification phase is to decide, to which class the unknown shape x belongs.

The set of pairs

$$\forall p = 1...k; R_p^x = \{(x, d_i^p) : d_i^p \in D_p\}$$

is created for each known class p, where unknown shape x is paired with all shapes d_i^p belonging to given class p.

The result class for the unknown shape x is determined using the nearest neighbor method. The class $cl(x)$ of the unknown shape x according the given database is then computed as

$$cl(x) = \arg \min_{r_p^x \in R_p^x} (f_p^*(r_p^x) \cdot c(f_p^*, r_p^x, \vartheta_p^*)),$$

where pairwise dissimilarity is computed using the class p best method normalized method f_p^*. There are used only the dissimilarity measures with shapes that are classified as similar by classifier and the best threshold ϑ_p^*. The pair with the lowest normalized dissimilarity measure is taken from all the pairs of the shape x and each shape from the database. The template shape from this pair denotes the resulting class.

Main advantage of this method is, that during the classification phase only one dissimilarity measure is computed for each pair. This significantly increases speed of the matching process in comparison to other combining methods, as they usually require to compute all the dissimilarity measures for each pair, as the computation of the dissimilarity measure can be very computational intensive.

3 EXPERIMENTS

Experiments are mainly conducted in context of place recognition, where the places are describe by shapes making use of laser range-finder sensors.

All shapes are represented by closed polygons. Four different datasets used in the experiments are described in following section. Examples of the shapes taken from used datasets are depicted on fig. 1.

Dissimilarity of the places is computed by different methods listed below. The methods providing dissimilarity of the shapes are selected to cover wide range of different approaches selected .

The proposed procedural knowledge-based method is compared to the AdaBoost method, as it is popular in robotics. The implementation of the AdaBoost.M1 from Matlab is used.

3.1 Datasets

Four datasets are used to show performance of the proposed method. The first dataset is a MPEG7 part B [8], which is commonly used for shape matching method comparison in pattern recognition and computer vision. This dataset is chosen as an ethalon, showing the performance of the presented method in context of shape retrieval problem. MPEG7 dataset contains binary images of different shape silhouettes. The MPEG7 dataset contains 70 different shapes each in 20 variants. To get the same format as in other datasets, the images are converted to polygons. Then the same set of methods is applicable to the all datasets.

The second dataset (called Robotic) is collected from a real environment by a mobile robot equipped with two real laser range finders Sick LMS200, in configuration providing together full 360 degree range scan. The robot is placed to 15 different places in an office building and the robot took 12 different scans around each place. These scans are taken equidistantly on the circular trajectory with $0.6m$ diameter, which ensures various orientations of the scans.

Two other datasets are generated synthetically in a robotic simulator. The third dataset called Box is generated from a planar environment, where boxes of various orientation and size are placed randomly. Then, 11 places are chosen and for each place 21 different range scans with varying orientation and displacement (limited to 1 meter) are generated. This dataset simulates a cluttered unstructured environment, but with lot of significant and detectable points (like corners).

The fourth dataset called Surface is generated from a 3D undulated surface. The range scans are generated in the same manner as in the Box dataset. This dataset simulated another type of unstructured environment without significant points.

3.2 Methods

Various methods suitable for place recognition from laser scans are used. As an initial source of methods is used work [9], where methods used in computer vision, shape matching and robotic mapping are compared. Selected methods are outlined in the following lines to provide main ideas of each method. For detailed description, see the original papers cited in each section.

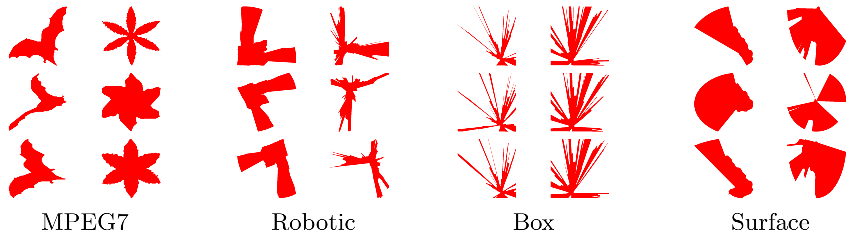

Fig. 1. Example of places from the used datasets.

Fourier Transformation (Fft) The shape is treated as a function in a polar coordinates system and is described by the coefficients of the Fourier transformation [10]. Only amplitudes of the Fourier coefficients are considered for the descriptor to assure a rotation invariance. To minimize influence of noise in the data, the only first 20 harmonic functions are considered. The dissimilarity of two descriptors is computed as the Euclidean distance in 20 dimensional space.

Tangent Space Traditionally, the closed polygon can be represented as a list of vertices or by giving a list of line segments. Alternatively, a polygon can be represented using a tangent space [11] - a list of angle-length pairs, whereby the angle at a vertex is an accumulated tangent angle at this point while the length is the normalized accumulated length of polygon sides up to this point. As the tangent space representation depends on the starting vertex, the dissimilarity of two polygons is a minimal difference between all possible variants of the tangent space representation.

Scan Line The scan line matching algorithm [12] computes a shape descriptor from the intersection of randomly placed lines with the polygon. All the intersecting points are ordered and form n compact intervals. The descriptor is a vector of values computed for different lengths of interval, where only intervals greater than given threshold are used. If an interval lies strictly on an interior or exterior of the polygon, the descriptor value is incremented. If the interval represents a collection of intervals both interior and exterior, the descriptor value is decremented. The dissimilarity of two polygons is a sum of absolute values of descriptors components difference.

Ring Projection The ring projection [13] algorithm computes the intersection of the polygon with the growing circle placed in the center of the polygon analogically to *Scan line* method. The value of ring projection is a fraction of circle part inside the polygon to circle circumference. The dissimilarity of two polygons is one minus a normalized correlation of polygon descriptors.

Integral Invariant The integral invariant method [14] relies on measurement of dissimilarity between two curves that represents an integral invariant of the polygon. The discrete version of integer invariant for a polygon is defined for a given vertex as a logarithm of sum of Euclidean distances from given vertex to all others.

The dissimilarity is computed in two steps: The best correspondence between the points of the polygons is computed at first. The distance between two descriptors is absolute value of difference of descriptors corresponding vertices.

Multi-scale Shape Representation (MRM) The multi-scale shape representation [15] stores convexity/concavity of the polygon at different scale levels for each point. Different scale levels for polygon are computed by the convolution with the Gaussian kernel. The convexity and concavity of the curve is measured as a displacement of the contour between two consecutive scale levels, which is measured as the Euclidean distance of the corresponding contour points from two consecutive scale levels. Dissimilarity is based on the cost of the optimal path found by the dynamic programming in the matrix of mutual points distances and normalized by complexity of the compared curves.

Fast laser interest region transform Fast laser interest region transform (FLIRT) method [16] is a multi-scale interest region operator for a 2D range data which combines the curvature-based detector with the β-grid descriptor. Interest points at the given scale correspond to points, where scale level equals the inverse of the local curvature of the smoothed signal. These interest points are described by β-grids. Place recognition using FLIRT is done by applying the RANSAC algorithm between two shapes. The re-projection error is used as the measure. The FLIRTLib [17] implementation is used in this paper with default parameters.

Shape context This method is based on assignment of a shape context [18] to each polygon vertex, which describes a near neighborhood of the vertex in question. The shape context is defined as a two-dimensional histogram of logarithmic polar distances from a particular vertex to other vertices in the polygon. The dissimilarity measure between two polygons can be then computed as follows: the shape context is computed for each vertex first and the shape distance between vertices of the two polygons are computed consequently. The distance between two polygons is obtained as the sum of distances between resulting matched vertex pairs.

Inner distance Inner distance method improves *Shape context* method described above. The inner distance of two vertices of the polygon is defined as a length of shortest path connecting the vertices under the condition that whole connecting path lies inside the polygon. The inner distance captures better the shape structure and is insensitive to articulation. Rest of the computation is same as in the *Shape context* method.

Geometric moments These methods compute the descriptors using geometric moments of the polygon, that are invariant to translation and scale [19]. Computation of the moments for polygon is well described in [20]. The dissimilarity of two polygons is computed as difference of corresponding moments normalized by the number of moments. In the experiments, the maximal order of polygon is set to 3, as the moments of higher order are sensitive to noise.

Zernike moments Contrary to the geometric moments, the Zernike moments are computed using complex polynomials that form an orthogonal basis [21]. The orthogonal moments allows computing arbitrary high moments of the input images. Similarily to the geometric moments or harmonics in Fourier transform, the low-order Zernike moments describe rough image properties, while the moments of higher orders are mainly influenced by detail in the image and therefore, they are more sensitive to noise. In this paper, Zernike moments of 15th order are utilized. For the details, see [22].

4 RESULTS

The performance of proposed method is evaluated on all four datasets. The speed and accuracy of the proposed procedural knowledge-based method is compared with AdaBoost.M1 method. The results of single shape matching methods are also depicted for comparison.

As place recognition methods are expected to work with a database, where more than one sensor reading is stored for each place, the cross-validation method is used to obtain results. There are n instances for each place in the dataset. The $n-1$ instances of each place are taken as the training set used for learning classifiers. Then the remaining instances of each place is taken as an unknown inputs and localized against the training set. This is performed n times for each place instance index.

The accuracy of the place recognition is measured using F-Score (Eq. 1). Results are depicted on figure 2 as boxplots, the bottom and top of the box are the first and third quartiles, and the band inside the box represents the median. The cross inside the box is a mean value of measured F-Scores. The ends of the whiskers represent the 9th percentile and the 91st percentile or the worst and the best cases respectively .

The performance of solving the retrieval problem is measured by so called Bull's eye score. This score expects that the dataset D can be divided into a set of k disjunctive classes $C = \{c_1, \ldots, c_k\}$; $\bigcup_{c \in C} c = D$; $\bigcap_{c \in C} c = \emptyset$ and each class $\forall c \in C, |c| = n$ has the same number n of shapes. Every shape is compared to all other shapes and the $m = 2n$ best matches are considered. The number of true positive hits h_i (both shapes are from same class) from the m best matches is computed for each shape $i \in D$. The Bulls eye score B is then the ratio of the total number of shapes from the same class to the highest possible number $B = \frac{\sum_{i \in D} h_i}{|D| n}$. Thus, the best possible rate is 100%.

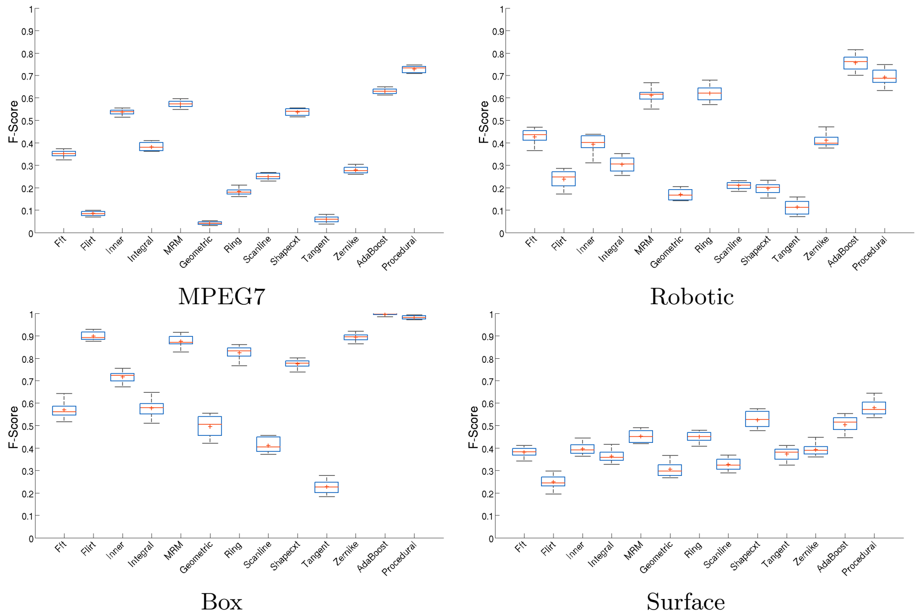

Fig. 2. F-Scores for datasets.

	Datasets			
Method	MPEG7	Robot	Box	Surface
FFT	0.52	0.52	0.58	0.52
FLIRT	123.59	191.23	993.00	657.43
Inner	42.49	17.81	37.46	52.88
Integral	0.65	1.60	0.88	0.97
MRM	162.29	87.63	140.86	139.37
Moments	0.69	1.46	3.24	4.37
Ring	2.20	4.46	25.53	11.49
Shapecontext	25.26	10.47	11.74	38.23
Scanline	47.51	70.79	125.97	195.46
Tangent	3.20	15.33	131.61	129.74
Zernike	164.52	65.30	103.60	129.47
AdaBoost	572.90	466.60	1574.50	1360.00
Procedural Knowledge	72.50	32.60	242.10	166.30

Table 1. Processing time [ms] of the classification phase.

	Datasets			
Method	MPEG7	Robot	Box	Surface
AdaBoost	475.19	7.16	11.57	6.61
Procedural Knowledge	102.78	3.65	4.17	4.17

Table 2. Learning time [s].

The results for the selected methods and datasets are summarized in the table 3. The best score is displayed in a bold font for each dataset, considering only the single shape matching techniques.

	Datasets			
Method	Mpeg7	Robot	Box	Surface
Inner	76.34	59.07	98.04	63.55
Fft I	65.40	72.22	78.54	57.43
Integral	48.21	51.99	83.24	50.38
Ring	34.84	81.20	**98.80**	52.34
Shapecontext	63.72	35.37	92.35	**70.95**
Zernike	47.98	64.26	97.67	55.62
Moments	16.97	36.39	74.81	51.27
Scanline	41.42	38.98	67.59	50.48
MRM	**77.95**	**81.76**	97.20	60.52
Tangent	18.38	30.37	39.08	58.94
Flirt	16.12	43.01	97.84	31.99
AdaBoost	91.32	94.19	99.99	56.56
Procedural Knowledge	92.89	92.68	99.46	80.11

Table 3. Bull's eye score.

The accuracy of the proposed procedural-knowledge based combining method is significantly higher than all the single shape matching methods. The average performance of the proposed method is always better than the best case performance of the best single method. This is a important property of the proposed method, addition of any even a very bad shape matching method cannot make an accuracy lower. This is not surprising as always the best possible method is used for particular place. Moreover, procedural knowledge-based method has no requirements on the properties of the partial methods in contrast to AdaBoost.

In comparison, a not suitable shape matching method can negatively influence the resulting accuracy of the AdaBoost method. AdaBoost requires that used partial methods performs better than random guess. This condition is not fulfilled when the Surface dataset is used, and AdaBoost fails to find good classifier for this dataset. As can be seen on the Surface dataset, the accuracy of the AdaBoost is lower than the best shape matching method. The accuracy of proposed method is comparable with the AdaBoost method on the other datasets.

A low computation time of the classification phase is a big advantage of the proposed procedural knowledge-based method. The computation time of the classification phase is crucial in the retrieval problem and place recognition task, as many partial comparisons are necessary to retrieve the shape class or localize the robot inside the known map. As the proposed procedural-knowledge based method utilizes only one dissimilarity computed by single method selected according the procedural knowledge, the computation time of procedural-knowledge based method is always lower (or equal), than the computation time of the slowest shape matching method. The number of used shape matching method does not influence the time consumption of the classification phase.

In comparison, the complex methods are typically worse than single method in term of time consumption, as they combine outputs from more than one shape matching method. The AdaBoost method needs the dissimilarity values computed by all methods, therefore the time consumption is increasing with every added shape matching method. The mean time necessary to compare one pair of places are summarized in table 1. The computation is performed in the Matlab on the computer with Intel Xeon 3.19Ghz computer with 8GB RAM.

The proposed procedural knowledge-based method is less time consuming than AdaBoost method, even in the learning phase. The time consumption to learn the AdaBoost classifier and the procedural knowledge-based classifier is summarized in the table 2. The size of learning set significantly influence the learning time as well as the number of used shape matching methods.

5 CONCLUSION

This paper presented a novel retrieval method based on the procedural knowledge. This method utilizes that the database is known in advance and chooses the best shape matching method for each class of shapes in database that distinguishes it from others. These chosen methods are called the procedural knowledge.

The utilization of the procedural knowledge significantly increase the accuracy of the retrieval problem and the place recognition task without additional computational costs. The performance of the novel method is always better than the best single shape matching method.

The procedural knowledge-based method require lower computation time in learning as well as in classification phase, in comparison to the AdaBoost method. This is caused by selecting only the one best classifier for each class of shapes, therefore during the classification phase, only one single dissimilarity measure is computed for each shape. Contrary, the AdaBoost requires to compute all the dissimilarity measures for each shape, which is time consuming.

The proposed method is suitable in all retrieval tasks, where the dissimilarity of unknown object with a database is required to compute, especially when the database is not homogeneous. In context of autonomous systems is it mainly the place recognition task and robot global localization. In these cases, the proposed procedural knowledge-based method provides the best results.

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