Journal of System Simulation

Volume 28 | Issue 12 Article 7

8-13-2020

Effective T2FPSO-Based T2FSVM Scene Classification Algorithm

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Keywords

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第 28 卷第 12 期 系统仿真学报© Vol. 28 No. 12
2016 年 12 月 Journal of System Simulation Dec., 2016

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Abstract: A systematic design methodology of Type-2 Fuzzy Particle Swarm Optimization (T2FPSO) based Type-2 Fuzzy Support Vector Machine (T2FSVM) classification system was proposed for scene image to improve selectivity and robustness in the machine vision. In the novel classification system, *the T2FSVM model was presented to realize a comprehensive learning* of the correct class and show the superiority of the generalization capability for classification problem. Furthermore, in order to improve the performance of PSO on complex uncertain environments, *the type-2 fuzzy concept was incorporated to PSO to construct T2FPSO searching algorithm*, in which the interval type-2 fuzzy inertia weight was designed using an Interval Type-2 Fuzzy Logic System (IT2FLS). Experimental studies indicate that the T2FPSO-T2FSVM approach is effective to deal with uncertainties for scene classification, when scene images are corrupted by the hybrid noises or captured by different view angels and light conditions.

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一种基于 T2FPSO 的 type-2 模糊支持向量机场景分类方法

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摘要：为提高机器视觉识别的选择性和鲁棒性，给出了基于 T2FPSO 优化的 T2FSVM 场景分类方法。算法中，设计了 *type-2 模糊支持向量机模型以提高其泛化能力*并得到正确的场景分类信息；为提高 PSO 在不确定环境中的优化能力，构建了融合 type-2 模糊集概念的 *T2FPSO 优化算法，并采用区间 type-2 模糊逻辑系统推理得到其惯性权值*。实验结果表明所提出的场景分类方法可对不确定信息进行有效处理。

关键词：场景分类；type-2 模糊粒子群优化；type-2 模糊支持向量机；type-2 模糊逻辑系统
中图分类号：TP391.9 文献标识码：A 文章编号：1004-731X (2016) 12-2925-09
DOI: 10.16182/j.issn1004731x.joss.201612007

Introduction

Recently, the topic of scene classification has got great attention from the scene processing community. This could be mainly proved by the fact that scene classification has been standing as an indispensable element for many practical applications, e.g., control of mobile robots [1-3], video understanding[4-6], and image processing[7-8]. Due to the huge complexity and diversity shapes in the scene[9-10], scene classification is difficult to obtain an effective and satisfied result

Received: 2016-02-26 Revised：2016-05-24;
Foundation item: The projects of Guangdong Natural Science Foundation (2014A030310380, 2015A030310257) , The project of Dongguan Polytechnic Foundation (2015a05)；
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for humanoid robot. Even the existing various noises, variations in view angle and lighting conditions, and dynamic backgrounds also lead to obstacles in selective and robust learning step. Up to now, scene classification is still a challenge problem for humanoid robot.

In the scene classification literature, several methods have been proposed for the understanding of scene images. Support Vector Machine (SVM)[11] SVM approach is a new tool for classification and estimation problems, which has been proved to possess the remarkable characteristics of good generalization performance, the absence of local minima, and sparse representation of solution. It is also less sensitive to the curse of dimensionality than traditional classification approaches. As a result, the SVM model has also been widely used in the real practical fields, such as pattern recognition[12-13], remote sensing[14-15], image segmentation[16-17] and sagittal balance and cooperation of robots[18-19]. Fuzzy Support Vector Machine (FSVM) has been designed to find a suitable fuzzy structure in the classification systems based on the concept of fuzzy set theory. However, these existing left out the undesirable uncertainties in the scene images, which are unfortunately ignored or have not been well discussed in the aforementioned works. A novel Type-2 Fuzzy Support Vector Machine (T2FSVM) framework is presented by integrating type-2 fuzzy theory to address this problem, which employed the type-2 fuzzy structure to express prior knowledge by the fuzzy domain to deal with the uncertainties.

Intelligent techniques have been integrated to SVM in order to improve the generalization and robust performance of SVM in recent years. Juang et al[20]. proposed an interval type-2 fuzzy neural network with support vector machine to endow the network with high generalization ability. Maulik et al[21]. integrated the Fuzzy C-Means Clustering (FCM) method to carry out as to establish the statistical significance of the proposed method in the FCM-SVM model, wherever a differential evolution (DE) based FCM clustering algorithm was proposed to categorical data analysis. Melgani et al[22]. proposed a Particle Swarm Optimization (PSO) based SVM system to improve the generalization capability of SVM, in which the classifiers are designed by searching for the best value of the parameters that tune its discriminant function and upstream by looking for the best subset of features that feed the classifier. However, these methods could not consider both the various noises and the variations of the view angle and lighting conditions in the scene images. Moreover, Type-2 Fuzzy Particle Swarm Optimization (T2FPSO) is not used in the previous literatures. A new T2FPSO searching algorithm is presented for the classifiers learning in the scene classification for humanoid robot.

In this paper, we proposed a systematic design methodology of Type-2 Fuzzy Support Vector Machine (T2FSVM) and Type-2 Fuzzy Particle Swarm Optimization (T2FPSO) classification for scene images to improve robustness and selectivity in the humanoid robot vision. In the first step, the T2FSVM system is presented to realize a comprehensive learning of the correct class and show the superiority of the generalization capability. In a second step, in order to improve the performance of PSO on complex multimodal problems, the type-2 fuzzy concept is incorporated to PSO to construct T2FPSO searching algorithm and design the interval type-2 fuzzy inertia weight using an Interval Type-2 Fuzzy Logic System (IT2FLS). Finally, a novel classification system based on T2FPSO is proposed to optimize further the performance of the T2FSVM classifier for the humanoid robot. The novel T2FPSO-T2FSVM classification algorithm is presented in Section 2, and the experimental results obtained on real scene data set are reported in Section 3, followed by the conclusion in Section 4.

1 T2FPSO-T2FSVM Classification System

The T2FPSO-T2FSVM classification algorithm could be divided into two parts: T2FSVM learning and T2FPSO searching. Ref to Fig.1. In the T2FSVM model, swarm vector was established by the T2FSVM parameters, and further used to obtain the suitable hyper parameters of the T2FSVM model and kernels. After that, the T2FSVM classification mechanism was built, which could be applied for the further scene classification and the T2FSVM classifier was employed to scene classification for the "Alice".

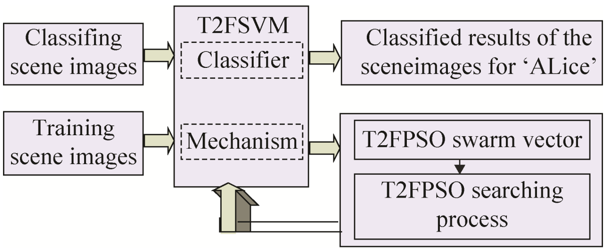

Fig. 1 The flowchart of the T2FPSO-T2FSVM classification algorithm

1.1 T2FSVM Learning Algorithm

Definition 1 *— Definition of Type-2 Fuzzy Support Vector Machine (T2FSVM)*: A type-2 fuzzy SVM model set, denoted $\tilde{\Xi}$, is characterized by a type-2 membership function $\mu_{\tilde{\Xi}}(D,u)$, where $D \in \Xi$ and $u \in V_D \subseteq [0,1]$. The T2FSVM set can be given as follows:

$$\begin{aligned}&\tilde{\Xi}=\{((D,u),\mu_{\tilde{T}}(D,u))|\\&\forall D\in\Xi,\forall u\in V_D\subseteq[0,1],0\leqslant\mu_{\tilde{T}}(D,u)\leqslant 1\}\end{aligned} \tag{1}$$

$\tilde{\Xi}$ could also be expressed as follows:

$$\tilde{\Xi}=\int_{D\in\Xi}\int_{u\in V_D}\mu_{\tilde{\Xi}}(D,u)\Big/(D,u) \qquad V_D\subseteq[0,1] \tag{2}$$

Since the objective functions of T2FSVM in the equations (1) and (2) were difficult to solve directly, T2FSVM model is firstly transferred to a group of Interval Type-2 Fuzzy Support Vector Machine (IT2FSVM). For simplicity, the upper and lower SVM models are employed to represent the IT2FSVM model, and the objective function can be described as follows:

$$\begin{aligned}&\min_{\bar{\varpi},\bar{e}}\ \bar{J}(\bar{\boldsymbol{\omega}},\bar{e})=\frac{1}{2}\bar{\boldsymbol{\omega}}^{\mathrm{T}}\bar{\boldsymbol{\omega}}+\bar{\gamma}\sum_{i=1}^{N}\bar{e}_i\\&\text{s.t. } y^{(i)}(\bar{\boldsymbol{\omega}}\cdot\bar{\varphi}(X^{(i)})+\bar{b})\geqslant 1-\bar{e}_i,\quad i=1,2,\cdots,N\end{aligned} \tag{3}$$

and

$$\begin{aligned}&\min_{\underline{\omega},\underline{e}}\ \underline{J}(\underline{\boldsymbol{\omega}},\underline{e})=\frac{1}{2}\underline{\boldsymbol{\omega}}^{\mathrm{T}}\underline{\boldsymbol{\omega}}+\underline{\gamma}\sum_{i=1}^{N}\underline{e}_i\\&\text{s.t. } y^{(i)}(\underline{\boldsymbol{\omega}}\cdot\underline{\varphi}(X^{(i)})+\underline{b})\geqslant 1-\underline{e}_i,\quad i=1,2,\cdots,N\end{aligned} \tag{4}$$

where $X^{(i)}$ and $y^{(i)}$ denote the feature to be classifying and the corresponding class label of the scene image i, respectively. $\bar{\gamma}$ and $\underline{\gamma}$ denote the regular parameters, and $\bar{e}_i$ and $\underline{e}_i$ denote the training errors of the upper and lower SVM model, respectively. With the Vapnik theory, the decisive function of the upper and lower SVM model could be deduced as:

$$\bar{D}(X)=sgn(\sum_{SVs}\bar{\alpha}_i y_i\bar{K}(X^{(i)},X)+\bar{b}) \tag{5}$$

and

$$\underline{D}(X)=sgn(\sum_{SVs}\underline{\alpha}_i y_i\underline{K}(X^{(i)},X)+\underline{b}) \tag{6}$$

where *sgn* denotes the sign function, and *SVs* denotes the Support Vectors for the corresponding SVM models. The searching algorithm for IT2FSVM would be designed to establish the whole theoretical classification algorithm for humanoid robot in the next section.

1.2 T2FPSO Searching Algorithm

Let $\bar{z}_j^t$ and $\underline{z}_j^t$ denote the upper and lower position vector, and $\bar{V}_j^t$ and $\underline{V}_j^t$ denote the upper and lower velocity vector of the j th particle in the swarm, respectively, at the time t. The updates functions of the interval particles in T2FPSO are realized according to the following equations:

$$\begin{aligned}\bar{V}_j^{t+1} &= \bar{\varpi}_j^t\bar{V}_j^t + \bar{c}_1\text{rand}_1 * (\bar{z}_j^* - \bar{z}_{j,h}^t) + \\ &\quad \bar{c}_2\text{rand}_2 * (\bar{z}^\wedge - \bar{z}_j^t) \qquad (7)\\ \bar{z}_j^{t+1} &= \bar{z}_j^t + \bar{V}_j^t\end{aligned}$$

and

$$\begin{aligned}\underline{V}_j^{t+1} &= \underline{\varpi}_j^t\underline{V}_j^t + \underline{c}_1 rand_1 * (\underline{z}_j^* - \underline{z}_j^t) + \\ &\quad \underline{c}_2 rand_2 * (\underline{z}^\wedge - \underline{z}_j^t) \qquad (8)\\ \underline{z}_j^{t+1} &= \underline{z}_j^t + \underline{V}_j^t\end{aligned}$$

where $\bar{z}_j^*$ and $\underline{z}_j^*$ denote the best upper and lower position vector of the j th particle up to time t, $\bar{z}^\wedge$ and $\underline{z}^\wedge$ denote the best upper and lower position vector the whole swarm up to time t, $rand_1$ and $rand_2$ are random numbers in [0,1]. $\bar{c}_1$ and $\underline{c}_1$ are the upper and lower individuality coefficients, and $\bar{c}_2$ and $\underline{c}_2$ are the upper and lower sociality coefficients, respectively. $\bar{\varpi}_j^t$ and $\underline{\varpi}_j^t$ are the upper and lower inertia weights.

Interval type-2 fuzzy sets are employed in the antecedent part of the IT2FLS, and Mamdani-type is used in the consequent part. The l th rule in the fuzzy system can be given as follows:

Rule l: if ϖ^t is $\tilde{B}_{l,1}$, AND ∂^t is $\tilde{B}_{l,2}$

then ϖ^{t+1} is $\tilde{O}_l$, $l = 1,\cdots,\Gamma$ (9)

where ϖ^t and ∂^t is the inertia weight and the fitness value, respectively, at time t. ϖ^{t+1} is the inertia weight for the next iterations t+1. $\tilde{B}_{l,k}, k = 1,\cdots,Kr$ is the interval type-2 fuzzy sets in the antecede part, $\tilde{O}_l$ is the output interval type-2 fuzzy set of the l th rule, and Γ is the number of fuzzy rules. According to the equation (9), the design of the interval inertia weight involves fuzzification, fuzzy rules, fuzzy inference engine, and type reduction. The interval type-1 fuzzy set of inertia weight could be displayed as follow:

$$\underline{\varpi}^{t+1} = \frac{\sum_{l=1}^{Ll}\bar{\lambda}_l\hat{\varpi}_l + \sum_{k=Ll+1}^{\Gamma}\underline{\lambda}_k\hat{\varpi}_k}{\sum_{l=1}^{Ll}\bar{\lambda}_l + \sum_{k=Ll+1}^{\Gamma}\underline{\lambda}_k} \qquad (10)$$

and

$$\bar{\varpi}^{t+1} = \frac{\sum_{l=1}^{Lr}\underline{\lambda}_l\hat{\varpi}_l + \sum_{k=Lr+1}^{\Gamma}\bar{\lambda}_k\hat{\varpi}_k}{\sum_{l=1}^{Lr}\underline{\lambda}_l + \sum_{k=Lr+1}^{\Gamma}\bar{\lambda}_k} \qquad (11)$$

where $\hat{\varpi}^{t+1} = (\hat{\varpi}_1^{t+1},\cdots,\hat{\varpi}_\Gamma^{t+1})$ denote the reordered sequent, with $\hat{\varpi}_1^{t+1} \leqslant \hat{\varpi}_2^{t+1} \leqslant \cdots \leqslant \hat{\varpi}_\Gamma^{t+1}$ and $\hat{\varpi}^{t+1} = \upsilon\varpi^{t+1}$, υ is an $\Gamma\times\Gamma$ permutation matrix, and $\bar{\lambda}_l$ and $\underline{\lambda}_l$ is the reordering results of the rule orders. Ll and Lr denote the left and right crossover points, respectively. K-M iterative procedure [19] can be used to find these two points.

Up to now, with type-2 fuzzy inputs of inertia weight and fitness value at time t, the corresponding inertia weight at time t+1 is deduced using an IT2FLS. The deduced inertia weight is then employed for the next iteration in the optimization process of T2FPSO-T2FSVM as shown in the next section.

1.3 Implementation of the Proposed T2FPSO-T2FSVM

In this section, T2FPSO-T2FSVM system for the classification of scene images was proposed for the humanoid robot. The position vector $z_j \in R^{d+3M}$ of j th particle Z_j from the T2F swarm is viewed as a vector establishing from a candidate subset of features among d available input features and the value of IT2FSVM classifier parameters. Let $\partial(j)$ denote the fitness function associated with the j th particle Z_j corresponding to SVs, ∂_j^t denotes the corresponding value at time t, for simplicity. The design of T2FSVM classifier with T2FPSO for classification problem includes the training and classifying process. The implementation of classification problem can be described as follows:

A. The Training Process

Step 1) Assigning the random upper and lower position vectors $\overline{z}_j (j=1,\cdots,\aleph)$ and $\underline{z}_j (j=1,\cdots,\aleph)$, and set the upper and lower velocity vectors $\overline{V}_j (j=1,\cdots,\aleph)$ and $\underline{V}_j (j=1,\cdots,\aleph)$ associated with the $\aleph$ particles to be zero.

Step 2) Suppose the initial position vector as the best position vector of each particle Z_j, which can be expressed as follows:

$$\overline{z}_j^* = \overline{z}_j (j=1,\cdots,\aleph) \tag{12}$$

and

$$\underline{z}_j^* = \underline{z}_j (j=1,\cdots,\aleph) \tag{13}$$

Step 3) For each upper and lower position vectors $\overline{z}_j \in R^{d+3M}$, $\underline{z}_j \in R^{d+3M}$, train the corresponding upper and lower IT2FSVM classifier and compute the corresponding upper and lower fitness function $\overline{\partial}(j)$ and $\underline{\partial}(j)$. The fitness value of the T2FPSO can be computed as follows:

$$\partial_j = \frac{\overline{\partial}(j) + \underline{\partial}(j)}{2} \tag{14}$$

If the current fitness value is smaller than that of best position vector, then set this position vector as the best position vector using the equations (12) and (13). Then to identify the particle that has the best fitness value described as $\overline{z}^\wedge$ and $\underline{z}^\wedge$.

Step 4) Updating the T2F velocity and position vectors of all particles using the equations (7) and (8).

Step 5) Repeat to Step 3) until a stopping criterion is met (If the maximum number of iterations is reached or a sufficiently good fitness value is obtained).

B. The Classifying Process

Select the best global position in the T2F swarm and train the upper and lower SVM classifiers $\overline{\mathrm{D}}(X)$ and $\underline{\mathrm{D}}(X)$, which are fed with the subset of detected features mapped by the best position vector and modeled with the upper and lower fitness values. We could classify the scene images based on the trained upper and lower SVM classifiers $\overline{\mathrm{D}}(X)$ and $\underline{\mathrm{D}}(X)$, which can be expressed as follows:

$$D(X) = \frac{\overline{D}(X) + \underline{D}(X)}{2} \tag{15}$$

2 Experimental Results

In this section, we carry out a set of experiments on our own real scenes and the OT data set to investigate the performance of the proposed T2FPSO-T2FSVM classification method. The control software platform of humanoid robot is designed on the operating system of Windows 7 and developed by the Matlab R 2009b to process and “understand” the scene images captured from robotic camera. In all experiments the size of scene images are normalized to fit in a 16×16 pixel box while preserving their aspect ratio. Classification Accuracy (*CA*) is served as the evaluation measure in our experiments, which is formally defined as follows:

$$P_{CA} = \frac{\#CN^i}{\#TN^i} (i=1,\cdots,6) \tag{16}$$

where $\#CN^i$ and $\#TN^i$ is the number of correctly classified scenes images and the total number of scenes images of the class i, respectively. The average *CA* of each classification algorithms would be taken as the performance measure to compare the state-of-the-art classification methods.

The first experiment was performed on our own real scene data set, which is composed of 6 scenes within three large scale evaluation data sets. As noises are always involved in the data measure channel and existed in the real applied environment, images are corrupted by the hybrid noises, impressed by variations in different view angles and lighting conditions for testing to validate the robustness of the proposed method. For each sample, the input feature vector consists of 256 values. Principal Component Analysis (PCA) is employed to reduce dimensionality of scene image representation for the further classifier learning, and T2FPSO optimization method is used for the different classification algorithms. In this work, we are focus on the scene images classification algorithm for humanoid robot. The optimal hyper-parameters and model parameters are the values that give the minimal fitness value. The whole process is repeated for ten times, which the different components are used for training in this paper. In order to justify the T2FSVM classifier, the proposed T2FSVM algorithm is compared to the SVM model with single RBF kernel, the Weighted Kernel (WK), and the Multiple Feature Kernel (MFK), respectively. The mean classification rate on the testing sets was listed in Tables 1~3. Table 1, Table 2 and Table 3 reports the results on the corrupted, different view angles, and different lighting conditions case, respectively.

Table 1 gives the classification results on the corrupted dataset. In this case, scene images are corrupted by the hybrid noises, wherein both Gaussian noise and impulse noise are involved in. Table 2 shows the experimental results on the newly built dataset under different view angles case and the similar results. Table 3 also reports the experimental results on the newly built dataset under different lighting cases. As shown in Tables 1-3, the T2FPSO-T2FSVM clearly outperforms than the conventional methods (RBF based SVM, WK-SVM and MFK-SVM), and multiple kernel WK-SVM and MFK-SVM methods outperforms than the traditional RBF based SVM. However, under the corrupted and variation in different view angles conditions, these methods would achieve lower CA, the reason is that the structure information of scene images is also destroyed.

Table 1 Experimental results on the newly built dataset under hybrid corrupted case %

Scenes	RBF SVM	WK-SVM	MFK-SVM	The Proposed T2FPSO-T2FSVM
Corridor	91.4	92.0	92.1	93.1
Lab	88.5	89.4	89.7	90.5
Office	92.2	93.2	93.5	93.8
Street	86.9	87.5	87.8	90.7
Corner	90.2	91.2	91.6	92.2
Landscape	90.1	90.5	90.8	91.9

Table 2 Experimental results on the newly built dataset under different view angles case %

Scenes	RBF SVM	WK-SVM	MFK-SVM	The Proposed T2FPSO-T2FSVM
Corridor	89.0	92.1	92.5	93.0
Lab	90.6	92.4	92.7	93.6
Office	88.3	91.5	91.5	91.9
Street	86.9	89.4	89.5	90.4
Corner	86.6	89.7	89.9	90.2
Landscape	86.5	89.3	89.5	90.5

Table 3 Experimental results on the newly built dataset under different light case %

Scenes	RBF SVM	WK-SVM	MFK-SVM	The Proposed T2FPSO-T2FSVM
Corridor	94.9	95.3	96.1	97.3
Lab	95.2	95.4	96.1	96.4
Office	96.7	96.8	96.9	97.5
Street	92.3	92.6	92.8	93.7
Corner	91.0	92.5	93.2	93.9
Landscape	90.2	91.4	92.6	92.8

We can also compare the efficiency of the RBF based SVM, WK-SVM, the MFK-SVM and the proposed T2FPSO-T2FSVM classification methods by calculating Computation Time (CT) on our own real scene data set. The average computing times of different classification methods under different cases would be shown in Table 4. The RBF SVM is almost 10 times more efficient than the presented T2FPSO-T2FSVM method, and the multiple kernel WK-SVM and MFK-SVM methods also performed better than the T2FPSO-T2FSVM in the training phase. Note that the training phase is always performed offline. The CT of these different classification methods was also highly similar in the classifying phase. The proposed T2FPSO-T2FSVM classification method yields over 92% classification rates under all cases, which would be provided us with the evidence to use the T2FPSO-T2FSVM for scene classification.

Table 4 Compare efficiency of different classification methods

CT(s)		RBF SVM	WK-SVM	MFK-SVM	The Proposed T2FPSO-T2FSVM
Corridor	Training	65.3034	93.2931	156.2594	683.2356
	Classifying	0.0208	0.0213	0.0215	0.0227
Lab	Training	74.2389	102.3027	198.4783	839.2948
	Classifying	0.0212	0.0219	0.0220	0.0227
Office	Training	79.3891	120.2848	206.3782	938.2830
	Classifying	0.0201	0.0204	0.0207	0.0211
Street	Training	69.2830	97.3940	173.0489	702.2839
	Classifying	0.0225	0.0228	0.0235	0.0240
Corner	Training	59.2930	85.3849	147.3975	538.3948
	Classifying	0.0215	0.0219	0.0224	0.0228
Landscape	Training	74.2930	128.3748	199.2746	826.4950
	Classifying	0.0236	0.0239	0.0245	0.0249

The second experiment was performed on the OT data set, which is composed of 8 scenes within one large scale data set and two small scale data sets. The large scale data set includes all scenes, in which scenes are classified into 8 categories. The small scale data sets both includes of 4 scenes (4 natural scenes and 4 man-made scenes, respectively), in which scenes are classified into 8 categories. For the comparison, the dimension of feature vector and the parameters of PCA algorithms are the same as the previous test. The proposed T2FSVM algorithm is also compared to the SVM model with single RBF kernel, the Weighted Kernel (WK), and the Multiple Feature Kernel (MFK), respectively. The mean classification rate of scenes on the large scale (all scenes) and two small scale (nature scenes and man-made scenes) data sets is listed in Table 5. It is observed that the proposed PFSVM-T2PSO approach is performed better than the SVM, RBF-SVM and MFK SVM classification methods in terms of classification accuracy. In addition, another observation is that the performance measurements are significantly improved by the application of T2PSO in the SVM model for the classifier learning.

Table 5 Experimental results on the OT data sets %

data sets	RBF SVM	WK-SVM	MFK-SVM	The Proposed T2FPSO-T2FSVM
Large scale	92.5	93.8	94.1	94.5
Nature scenes	91.8	92.9	93.6	94.2
Man-made scenes	93.2	93.7	94.5	95.3

3 Conclusion

Type-2 Fuzzy Particle Swarm Optimization (T2FPSO) and Type-2 Fuzzy Support Vector Machine (T2FSVM) classification for scene images is proposed to improve selectivity and accuracy in the humanoid robot vision. Different noises, and variations in view angle and lighting condition could be taken as the uncertainties in the scene classification systems. The proposed systematic design methodology of T2FPSO-T2FSVM not only extended the traditional SVM into three-domain (fuzzy, input, and Hilbert spaces) structure in order to provide a feasible solution to treat input-Hilbert signals and fuzzy uncertainties together in the T2FSVM model, but also incorporated the type-2 fuzzy concept into PSO, in which the interval type-2 fuzzy inertia weight was deduced by the type-2 fuzzy logic system in the T2FPSO searching structure. The experimental results certainly confirm that the T2FSVM approach was robust and superior compared to the traditional SVM methods and suggest that further improvements in terms of Classification Accuracy(CA)could be achieved by the proposed T2FPSO-T2FSVM classification system in the uncertain environments. In the future work, we would like to improve the design of the membership function in the T2FSVM model and the computational efficiency in the T2FPSO searching process to make our classification method more robust and can apply the proposed system to the more challenging scenes.

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