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1 A novel semisupervised SVM classifier based on active learning and 2 context information

3 Fei Gao · Wenchao Lv · Yaotian Zhang · Jinping Sun · Jun Wang · Erfu Yang

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6 Abstract This paper proposes a novel semisupervised support vector machine classifier (S³VM) based 7 on active learning (AL) and context information to solve the problem where the number of labeled 8 samples is insufficient. Firstly, a new semisupervised learning (SSL) method is designed using AL to 9 select unlabeled samples as the semilabled samples, then the context information is exploited to further 10 expand the selected samples and relabel them, along with the labeled samples train S³VM classifier. 11 Next, a new query function is designed to enhance the reliability of the classification results by using 12 the Euclidean distance between the samples. Finally, in order to enhance the robustness of the proposed 13 algorithm, a fusion method is designed. Several experiments on change detection are performed by 14 considering some real remote sensing images. The results show that the proposed algorithm in 15 comparison with other algorithms can significantly improve the detection accuracy and achieve a fast 16 convergence in addition to verify the effectiveness of the fusion method developed in this paper.

Keywords semisupervised support vector machine · active learning · context information · remote
 sensing

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1 1 Introduction

2 With the rapid development of remote sensing (RS) technology, RS data has been expanded constantly and used widely in geologic monitoring, environmental protection and disaster relief, where the 3 4 distinction of the land-cover change(Hansen and Loveland 2012), classification of the land-use(Gong et 5 al. 2015) and assessment of the earthquake influence(Geiß and Taubenböck 2013)can be attributed to the problem of object detection under certain conditions. In these fields, it is a very difficult task to 6 7 detect useful objects from a large amount of RS images (RSIs), which presents a high requirement to 8 the information extraction ability of the correlated algorithms and increasingly attracts the research 9 interest.

10 The traditional technologies for object detection are mainly based on unsupervised learning and 11 supervised learning. Unsupervised method detects the object from its background via grouping the 12 samples into different clusters and does not require prior knowledge, which reduces the time and cost 13 for human-labeled training samples. However, such methods only consider the characteristic 14 information between the different clusters and lack the effective guidance of the labeled samples, 15 which makes it impossible to extract objects of interest(Anand et al. 2014). Therefore, the supervision 16 method based on the labeled samples is adopted to change the detection problem into classification 17 problem and quickly captures the effective RS information with the high accuracy. However, to train 18 the classifier, the supervised method requires enough labeled samples(Ujjwal Maulik and Chakraborty 19 2012), which are scarce in practice and easily affected by noises. Moreover, it is very difficult to obtain 20 the labeled samples manually because of the limit of the time and cost (Li et al. 2010). In contrast, the 21 unlabeled samples are abundant and contain a wealth of information. By using them, not only the 22 problem of insufficient training samples can be solved, but also the working efficiency is 23 improved(Shahshahani and Landgrebe 1994). Therefore, in recent years the algorithms based on the 24 semisupervised learning (SSL) have been concerned greatly.

25 The SSL based method iteratively selects the unlabeled samples with the labeled samples together to 26 train the classifier(Kawakita and Kanamori 2013), and can reduce human intervention and classify the 27 unlabeled samples more effectively. In general, the SSL can be grouped into the following five 28 categories, i.e.: self-training, cooperative training, generative probability model, semisupervised 29 support vector machine(S³VM) and graph based methods(Chapelle et al. 2006; Zhu 2010), where the key to their effective functioning is the way for screening the unlabeled samples. The progressive 30 31 S³VM with diversity (PS³VM-D) takes γ samples which are within and closer to the margin band, to 32 define the candidate semilabeled samples, then incrementally selects ρ diverse samples among the γ 33 candidates by considering the kernel cosine-angular similarity(Persello and Bruzzone 2014). The 34 context-sensitive S³VM (CS⁴VM) selects the context patterns of training samples as the semilabeled 35 samples, then weights them depending on their consistency with the center sample by SVM(Bruzzone 36 and Persello 2009). Junwei et al. (2015a) built a high-level object feature representation using a deep 37 Boltzmann machine(DBM) and applies the proposed Bayesian principle to characterize the objects 38 information, then classifies the objects by the liner SVM to select the semilabeled samples.

The performance of the SSL algorithms can still be improved in the following aspects. First, the SSL based methods can be deteriorated when exploiting huge amount of the unlabeled samples, which

would seriously hinder the adjustment of the relevant parameters(Munoz-Mari et al. 2012;
 Gomez-Chova et al. 2008), and the effective strategy for the selection of the semilabeled samples is
 necessary. The SSL based methods can be greatly affected by initial training set(Didaci et al. 2012),

4 where the validity of samples can't be guaranteed sometimes, leading to random classification result.

5 For the selection strategy of the semilabeled samples, Pasolli et al. (2014) applied the active learning (AL) and the spatial information, including Parzen window, spatial entropy, etc., to process the 6 7 unlabeled samples, where the semilabeled samples were selected by estimating the probability density 8 distribution function of the random variables and the entropy of the discrete random variables. Demir et 9 al. (2011) applied the AL based on kernel clustering to deal with the unlabeled samples, then designed a 10 new strategy to select the most representative semilabeled samples. Inspired by the above algorithms, 11 the selection strategy was designed utilizing AL in the proposed SSL based algorithm. The AL 12 iteratively extracts the most informative unlabeled samples to be labeled manually and can obtain a 13 higher classification accuracy than other SSL algorithms, reducing the dependence on the labeled 14 samples (Tuia et al. 2011; Persello and Bruzzone 2014). However, the existing feature descriptors are 15 insufficiently powerful to characterize the information of objects, which inevitably leads samples 16 mislabeling and seriously reduces the classification accuracy. To fully describe the sample 17 characteristics, Junwei et al. (2015b)proposed a novel framework via the deep learning methods for the 18 salient object detection, which extracts four neighborhood image boundaries of the object as a 19 reference, then applied the stacked de-noising auto-encoder(SDAE) with the deep learning 20 architectures to model image background. The robustness of the mislabeled patterns is improved by 21 exploiting spatial information. Inspired by the above method, the structure of the AL is modified by 22 using the context information, which can expand the amount of semilabeled samples and improve the 23 accuracy to a certain extent when labeling them.

The reason why the S³VM is chosen to process the selected samples is detailed in the following. The support vectors of S³VM make the decision rather than many redundant samples to improve the operational efficiency and the robustness to the polluted samples. The nonlinear mapping based S³VM can map the samples into a high dimensional characteristic space to make them linearly separable. The functional margin that is the distance between the sample and the optimal hyper plane decided by the S³VM, can be used as the confidence-based decision marking to make the S³VM be effectively exploited by the SSL based methods(Hearst et al. 1998; U. Maulik and Chakraborty 2014).

For the uncertainty of the initial training set, the fusion is an effective method. The downsampling is commonly used to obtain different data models by generating the images at different resolutions(Bazi

et al. 2010). However, the progressively downsampling is not suitable to deal with the image with large difference in areas, because it can lose them with scanty pixels. The initial sets in the SSL does not require many labeled samples, so they can be directly selected from the image to reduce the complexity of the preprocessing. Their SSL results as different models were fused to decrease the influence of the random distribution of the initial set and obtain stable classification result.

38 In this paper, a novel $S^{3}VM$ algorithm is proposed to address the classification problems of the RSIs

39 when the available labeled samples are not sufficient. To guarantee the decision-making ability of the

40 proposed method, the AL and context information are applied to select the informative unlabeled

1 samples (semilabeled samples), which are combined with the labeled samples together to train the 2 S³VM. The novelty of this paper lies in the following aspects. First, a new query function is designed 3 based on the Euclidean distance among samples. Second, the amount of the semilabeled samples are 4 increased by exploiting their contextual patterns. Last, the selected samples are relabeled by exploiting 5 the correlation between the sample and context. Hence, the comprehensive utilization of the context 6 information ensures the reliability of the selected samples and increases the classification credibility of 7 the S³VM. 8 The rest of this paper is organized as follows. Section 2 describes the proposed SSL based method in

9 detail, and the necessity of the fusion is also analyzed to design new fusion rules. Section 3 presents the

three data sets and experiments for the RSIs change detection. Section 4 draws the conclusion of thispaper.

12 2 Proposed method

13 The algorithm consists of two parts: the proposed S³VM based on AL and context information, and the 14 fusion method.

15 2.1 Proposed SSL-based method

Assuming that the training set Lis composed of n pairs (x_i, y_i) available, where x_i denotes the training samples and $y_i \in \{+1, -1\}$ denotes the label for the binary classifier. We assume that a learning set U with m unlabeled samples (x'_i) . They are defined as

$$\mathbf{L} = \{ (\mathbf{x}_i, \mathbf{y}_i) \mid i = 1, \dots, n \}$$

$$\tag{1}$$

(2)

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21 In order to expand L, the semilabeled samples are selected from U iteratively. Fig. 3 shows the

 $U = \{x'_i \mid j = 1....m\}$

22 flowchart of the SSL method based on the S^3VM .



23

24 Fig. 1Flowchart of the proposed method

1 First, L is processed by the $S^{3}VM_{1}$, during which the label Y of the U is obtained. The subset (U₁, Y₁) is

2 selected by the query function Q. Then, the context patterns U_2 of the U_1 is found from the U and

3 classified by the S^3VM_2 . U₂along with the central pattern (U₁, Y₁) are relabeled by H to get the

4 semilabeled set (U_3, Y_3) . Last, the repeated samples between Land (U_3, Y_3) are eliminated to obtain the

5 ultimate semilabeled set $L_1 = (U_4, Y_4)$ to be added into L. The entire process is iterated until the

6 predefined convergence condition is satisfied, e.g., the total number of the semilabeled samples or the

7 classification accuracy is reached (Pasolli et al. 2014).

8 Next, the implementation of the $S^{3}VM$, the query function Q, the search contextual patterns and

9 relabeling strategy H are described.

$10 \quad 2.2S^{3}VM \text{ method}$

16

The S³VM is the expansion of the SVM. A standard SVM is based on the structural risk minimization to classify the learning set by extracting the support vectors from the training set to find the optimal hyper plane(Scholkopf et al. 1997). In case of the binary SVM, given the training set Land the testing set U, it is limited to the following constrained optimization problem (Izquierdo-Verdiguier et al. 2013):

$$\min \Psi(\mathbf{w}) = \frac{1}{2} (\mathbf{w}^{\mathrm{T}} \mathbf{w}) + C \sum_{i=1}^{n} \xi_{i}$$

Subject to : $y_{i} [\mathbf{w}^{\mathrm{T}} \Phi(\mathbf{x}_{i}) + b] \ge 1 - \xi_{i}$ $i = 1, ..., n$
 $\xi_{i} \ge 0$ (3)

Where x_i is the training sample and y_i is the corresponding label,(x_i,y_i)∈ L;Φ(·) maps the data into the
feature space; w is the orthogonal vector between x_i and the hyper plane; b is the bias to measure
the distance between L and the hyper plane; ζ_i is the slack variable to represent offset of x_i; Cis the cost
factor to measure the weight between the optimal hyper plane and the minimum offset; n is the number
of the training samples.
After the initialization, the iterative process is operated and the semilabeled samples (selected from U

in the previous step) are added to **L**. Their confidence is diverse in different iterative steps and they are given different cost factors(Bovolo et al. 2008), which leads to the following cost function for the classifier learning :

26

$$\min \Psi(\mathbf{w}) = \frac{1}{2} (\mathbf{w}^{\mathrm{T}} \mathbf{w}) + C \sum_{i=1}^{n} \xi_{i} + \sum_{j=1}^{m} C_{j} \Box \varepsilon_{j}$$
Subject to : $y_{i} [\mathbf{w}^{\mathrm{T}} \Phi(\mathbf{x}_{i}) + \mathbf{b}] \ge 1 - \xi_{i}$ $i = 1, ..., n$

$$\hat{y}_{j} [\mathbf{w}^{\mathrm{T}} \Phi(\hat{\mathbf{x}}_{j}) + \mathbf{b}] \ge 1 - \varepsilon_{j}$$
 $j = 1, ..., n'$

$$\xi_{i} \ge 0, \varepsilon_{j} \ge 0$$

$$(4)$$

where \hat{x}_j is the semilabled sample selected from **U**, with the slack variable(ε_j), cost factor (C_j) and semilabel(\hat{y}_i), and n'is the number of the semilabeled samples.

29 Applying the Lagrange Duality, the equation (4) can be transformed into the dual problem, which can

30 be solved by applying the Karush–Kuhn–Tucker(KKT)(Yi et al. 2011)optimality conditions:

$$\max_{\alpha,\beta} \left(\sum_{i=1}^{n} \alpha_{i} + \sum_{j=1}^{m} \beta_{j} - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_{i} \alpha_{j} y_{i} y_{j} K(x_{i}, x_{j}) - \frac{1}{2} \sum_{i,j=1}^{m} \beta_{i} \beta_{j} \hat{y}_{i} \hat{y}_{j} K(\hat{x}_{i}, \hat{x}_{j}) - \sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{i} \beta_{j} y_{i} \hat{y}_{j} K(x_{i}, \hat{x}_{j}) \right)$$
Subject to:
$$\sum_{i=1}^{n} \alpha_{i} y_{i} + \sum_{j=1}^{m} \beta_{j} \hat{y}_{j} = 0$$

$$0 \le \alpha_{i} \le C$$

$$i = 1, \dots, n$$

$$0 \le \beta_{i} \le C,$$

$$j = 1, \dots, m$$
(5)

where $K=(x_i, \hat{x}_{jj})$ is a kernel function to calculates the inner product $\langle \Phi(x_i) \cdot \Phi(\hat{x}_j) \rangle$; α_i and β_j are the Lagrange multipliers corresponding to the labeled sample (x_i) and the semilabeled sample (\hat{x}_j) respectively. When α_i and β_j are solved by(5), b is solved by

$$f(x) = \mathbf{w}^{T} \bullet \phi(x) + b = \left(\sum_{i=1}^{n} a_{i} y_{i} K(x, x_{i}) + \sum_{j=1}^{m} \beta_{j} \hat{y}_{j} K(x, \hat{x}_{j})\right) + b$$
(6)

6 Finally, the unlabeled sample $x (x \in U)$ can be labeled by the following decision function:

$$y' = sgn\{(\mathbf{w}^{T} \bullet x') + b\} = sgn\left\{\left(\sum_{i=1}^{n} a_{i} y_{i} K(x', x_{i}) + \sum_{j=1}^{m} \beta_{j} \hat{y}_{j} K(x', \hat{x}_{j})\right) + b\right\}$$
(7)

8 It is worth noting that with the increase of iteration, the previous semilabeled samples are more 9 convincing and the corresponding C_j would get bigger. The S³VM can deal with the nonlinear problem 10 using many different kernel functions, such as Gauss kernel function, radial kernel function or 11 exponential kernel function.

12 The basic structure of the S^3VM is described above. The learning set U and the result Y classified by 13 the S^3VM_1 are the inputs to Q that is described next.

14 2.3Query Strategy Q

Fig. 2 shows the structure of the query strategy Q consisting of two parts Q_1 and Q_2 . Q_1 is used to screen (U', Y') from (U, Y). Then, (U', Y') is refined by Q_2 using the proposed rules f_1 and f_2 , and the output is(U₁, Y₁).



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19 Fig. 2Structure of Q

20 2.3.1 The implementation of Q_1 and Q_2

21 Q₁is designed on the basis of the MS. The MS is conducive to the convergence of the algorithm 22 because the samples within the margin band are more informative than others. Therefore, U'is selected 23 within the margin band, where the absolute value of the decision function is limited between the ρ and 24 1, defined as follows:

1	$\mathbf{U}' = \left\{ \mathbf{x}_i \mid \mathbf{x}_i \in \mathbf{U}, \rho < abs(value_i) < 1, i = 1,, m \right\}$ Subject to : value _i = f(x _i) = $\mathbf{w}^T \Box \mathbf{x}_i + b$ (6)	(8)
2	Q2is designed by using the Euclidean distance between the samples and the screening samples from the	he
3	U'by applying the rules f_1 and f_2 . The implementation is shown as follows:	
4	I. The distance (\mathbf{D}) between the sample of U'and the training set L is calculated by	
5	$\mathbf{D} = \{ \mathbf{d}_{ij} \mid \mathbf{d}_{ij} = \operatorname{norm}(\mathbf{x}_i, \mathbf{x}_j), \mathbf{x}_i \in \mathbf{U}', \mathbf{x}_j \in \mathbf{L} \} $	9)
6	II. The minimum, maximum and their ratios between U' and L are calculated by	
7	$\mathbf{D}_{\min} = \left\{ \mathbf{d}_{i} \mid \mathbf{d}_{i} = \min_{j} (\mathbf{d}_{ij}), \mathbf{d}_{ij} \in \mathbf{D} \right\} $ (1)	0)
8	$\mathbf{D}_{\max} = \left\{ \mathbf{d}_{i} \mid \mathbf{d}_{i} = \max_{j} \left(\mathbf{d}_{ij} \right), \mathbf{d}_{ij} \in \mathbf{D} \right\} $ (1)	1)
9	$\boldsymbol{\Delta} = \left\{ \boldsymbol{\delta}_{i} \mid \boldsymbol{\delta}_{i} = \frac{\mathbf{D}_{\min}(i)}{\mathbf{D}_{\max}(i)} \right\} $ (1)	2)
10	III. The rule f_1 is used to select x_1 from U':	
11	$f_{i}: x_{i} = \mathbf{U}'(i)$ Subjected to: $\mathbf{D}_{max}(i) = max(\mathbf{D}_{max}), i = 1,, k$ (1)	3)
12	IV. The rulef ₂ is used toselectx ₂ fromU':	
13	$f_2: x_2 = \mathbf{U}'(i)$ Subjected to: $\mathbf{\Delta}(i) = \max(\mathbf{\Delta}), i = 1,,k$ (1)	4)
14	V. Finally, update U ₁ :	
15	$\mathbf{U}_1 = \mathbf{U}_1 + \mathbf{x}_1 + \mathbf{x}_2 \tag{1}$	5)
16 17	Through the loop running I-V, U_1 is updated continuously until the number of samples in U_1 reach the threshold.	es

The implementation of Q has been introduced. Next, the significance off₁ and f₂ is described to prove
the rationality of Q.

- 20 2.3.2 Significance of f₁ and f₂
- 21 In order to facilitate the description, Fig.3 illustrates the distribution of the sample $x(x \in U')$ and the
- 22 training set L.



23 24

Fig. 3Distribution of the sample x and training set L. (a) x distributed around E_3 randomly. (b)x distributed in the direction of the short axis of E_3 . (c)x distributed in the direction of the long axis of E_3 .

For all the figures in Fig.3, **L** is shown as the blue dots and E_{3} is the boundary; x is shown as the black dots, $d_{1} \in \mathbf{D}_{min}$ and $d_{2} \in \mathbf{D}_{max}$ (shown in the equation(10) and (11)); the points in E_{1} have the same

29 minimum distance with d_1 ; the points in E_2 have the same maximum distance with d_2 .

1 For the f_1 , Fig. 3(a) shows that the bigger d₂generates a longer distance between x and L, and a smaller 2 probability of x belonging to L, so more information is contained in xwhich can decrease the amount 3 of the semilabeled samples used by the SSL. Therefore, f_1 can select the informative sample and reduce 4 the semilabeled samples to the greatest extent. For the f₂,Fig. 3(a) shows that the δ ($\delta \in \Delta$,in (12))in x can be written as 5 6 $\delta = d_1/d_2$ (16)7 In order to facilitate the description of f_2 , the expression of δ needs to be changed. 8 Let: $d_1 = d_2 - t$ (17)9 Where t is the secant of x in E_3 , then substitute (17) into (16): 10 $\delta = (d_2 - t)/d_2$ (18) $\delta = 1 - t/d_2$ (19)11 Get: 12 where it can be seen that: when d_2 is invariant, the bigger δ is, the smaller t is, which means that x

would be closer to the short axis of E_3 (shown in Fig. 3(b)) and can make distribution of L more uniform (compared with Fig. 3(c));when t is constant, the bigger δ is, the smallerd₂is, and the longer distance between x and Lis, which means that the smaller of the probability of x belonging to the L, so the more information that x contains. Therefore, f₂cannot only reduce the semilabeled samples by selecting informative ones, but also make the distribution of L better.

18 2.4Search contextual patterns

This function makes the current pixel $x(x \in U_1)$ as the center sample to find the context patterns U_2 from the neighborhood. There are many choices for U_2 . Espinola et al. (2015)introduced the most common types shown in Fig.4, where Von Neumann neighborhood and Moore neighborhood are called the first-order system and the second-order system(Bruzzone and Persello 2009), and Von Neumann neighborhood is also called the four-directly neighbored pixels (Zhao et al. 2013).



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Fig. 4 Examples of neighborhood systems. (a) Von Neumann neighborhood, (b) Moore neighborhood and (c) Extended Moore neighborhood

Context information is very significant. Firstly, the center sample and the context patterns are close in the space, which makes their characteristics exist great relevance that can be applied to calculate the image texture feature(D'Elia et al. 2014)or generate the classification map(Bruzzone and Persello 2009).

31 More semilabeled samples are found using context information, which can improve the convergence

32 speed for the SSL. Secondly, their labels can also provide very important information. In(Espinola et al.

33 2015), the cell automaton distinguishes the different pixels (such as the boundary, noise, or common) at

34 each iteration by utilizing their labels. The robustness of the SSL algorithm can be increased by

- 1 properly using the context information of labels. The next section describes the way to relabel samples
- 2 by using the information of labels.
- 3 2.5 H: Relabeling samples
- 4 Q selects the samples between the maximum margin bands, where the selected samples are more likely 5 to be contaminated and mislabeled manually. To increase the reliability of the selected samples, the 6 central samples (U_1, Y_1) and the context patterns (U_2, Y_2) are relabeled by the function H with the
- 7 following rules:
- 8 I. When Y₂are consistent with Y₁, they are left;
- 9 II. When Y_{2} are inconsistent with Y_{1} , Y_{1} is incorrect. To make L representative, the corresponding 10 central sample is discarded and the context patterns are left.
- 11 III. When a part of Y_2 is consistent with Y_1 , for Y_2 , the inconsistent context patterns are removed; for Y_1 ,
- the proportion of consistent part to context patterns is calculated: if the proportion is greater than the threshold, rules A would be followed, else rules B would be chosen.
- 14 The semilabeled set (U_3, Y_3) is obtained after being relabeled by H. Then, those samples repeated with
- 15 L are eliminated, which generates the semilabeled set $L_1 = (U_4, Y_4)$ to add to L.
- 16 Section 2.1-2.5 describes the proposed SSL based method. In order to overcome the influence of the
- 17 randomness of the learning set L, the classification results are fused in the next section.

18 2.6Fusion method

Data fusion is a very popular data processing technology to make up for the defects caused by the missing data or noise pollution. It can be used in many methods. The principal component analysis (PCA) extracts the principal components to fuse the training set, and the spectral information and spatial information are combined together to fuse images. Our fusion method is shown in Fig.5, where the part in the dashed rectangular box is the SSL based method proposed in Section 2.1:



- 24
- 25 Fig. 5Fusion method
- Firstly, because only a few labeled samples are needed to initialize the training set, the initial L (L' and etc.) are selected from the **DATA** manually and would not cost a lot. Then, L is processed by the proposed method to classify the learning set U for obtaining the classification result Y. The other initial sets are processed by the same way. Finally, the different classification results (Y,Y'and etc.) are treated as the different data models to be fused by the given different weights based on the detection accuracy.

1 3 Experiments

In this section, the related experiments are designed to measure the performance of the proposed algorithm (Method Proposed, PM) in three aspects. Firstly, to compare PM with the supervised algorithm, the experiments on PM and SVM are carried out. Secondly, to compare PM with the semisupervised algorithm, the experiments on PM, CS⁴VM and PS³VM-D are carried out. Finally, to further improve the performance of PM, the different experimental results are fused.

7 3.1 Dataset description and parameters setting

8 3.1.1 Dataset Description

9 Our experiments on change detection are performed on real RSIs, as shown in Fig. 6, where the regions 10 A and regions B indicate the changed regions and unchanged regions respectively. The aim of change 11 detection is to distinguish the changed part and unchanged part of images (Habib et al. 2009; Celik 12 2010), and can be regarded as the binary classification problem. For the regions A: Fig. 6(a)-(b) are the 13 city images taken before and after the earthquake and possess the rich texture features because of many 14 artificial constructions. The change is due to the accumulation of people. Fig. 6(c)-(d)are the ground 15 images taken at different periods and do not possess obvious texture features. The change is due to the 16 appearance of many white patches. Fig. 6(e)-(f)are the coast images taken at different periods and also 17 do not possess obvious texture features. The change is due to the appearance of a few small-scale gray 18 patches. For the regions B of Fig.6, their geomorphic features are unchanged basically, only the gray 19 changes a little.



Fig. 6 Remote sensing images of the city (a) before earthquake and (b) after earthquake, the ground (c) before change and (d) after change, and the coast (a) before change and (b) after change. A represents the changed areas, B represents the unchanged areas

3 co-occurrence matrix is calculated as the **DATA**₁; for Fig. 6(c)-(d) and Fig. 6(e)-(f), the sample texture 4 features are calculated as the DATA2 and DATA3 respectively. All the experimental data are normalized 5 and divided into the training set and the learning set respectively. 6 3.1.2Parameters setting 7 The cost factor C of the PM is nonlinear, defined as follows: 8 $\mathbf{C} = \boldsymbol{\alpha} \bullet (\mathbf{N} - 1)^2 + \mathbf{C}_1$ (20)9 Where N is the number of iterations; C_1 is the initial cost factor; α is the weight coefficient. α and C_1 are 10 set to 1, and the change range of C is [1,100]. With the increase of iterations, the reliability of the 11 selected samples would increase, and the corresponding C would become larger than the previous one. 12 For the PS³VM-D, C is shown in (20), where C_1 is set to 2 and α is calculated by 13 $\alpha = (C_{max} - C_{min}) / (r - 1)^2$ (21)14 Where C_{max} and C_{min} are the maximum and minimum of C; r is designed artificially, with r = 10 herein. 15 For the CS⁴VM, C is defined as: 16 $\mathbf{C} = 2 \bullet (\mathbf{N} - 1) + \mathbf{C}_1$ (22)

After all the images are processed by the geometric registration and radiometric calibration, then the

ratio map of grayscales is generated. To characterize the images, for Fig. 6(a)-(b) the gray level

17 where N is also the number of iterations; The initial value of C_1 is 2. C is weighted by the K

18 K=C/C'=2 (23)

When the label of the contextual pattern is the same as the center sample, C is exploited, otherwise C'is explored.

21 All the methods are performed using the Gauss kernel function, with the radial width set 0.6. The Von

22 Neumann neighborhood is applied by the PM and CS⁴VM.

- 23 3.2 Comparison with SVM
- 24 Considering the DATA₁, the performance of the SVM and PM is compared. Fig. 7 shows the detection
- 25 grayscales of the two algorithms.



Fig. 7 Detection grayscales achieved on DATA₁in terms of (a) SVM and (b) PM.A represents the changed areas, B represents the
 unchanged areas

30 Through the threshold processing, the detection maps are obtained, as shown in Fig. 8 where the

31 white area is detected with the changes and the black area is detected as unchanged; A represents the



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1 changed areas and the B represents the unchanged areas.



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4 Fig. 8 Detection maps achieved on the DATA₁ in terms of (a) SVM and (b) PM, where the white area is detected with the 5 changes and the black area is detected as unchanged; A represents the changed areas and the B represents the unchanged areas 6 There is much omission in A and false alarm in B in Fig. 8(a), while the detection error is much less in 7 Fig. 8(b). In order to compare the performance of the PM in detail, 6 experiments of PM were 8 implemented to obtain the results in terms of the overall accuracy (OA) and Kappa, as shown in Fig. 9.



10 11 Fig. 9 Results achieved on DATA1 in terms of (a) OA and (b) Kappa

12 From Fig.9, except the results of the fifth experiment in which the PM are slightly lower than the SVM, 13 others are significantly higher than the SVM in OA and Kappa. Therefore, in comparison with the 14 SVM, the detection accuracy and performance of the PM have been improved greatly.

15 The training set of the SVM is obtained by the threshold segmentation. The threshold must be large 16 enough to ensure the accuracy of the training set, which means that the samples with a high diversity 17 are probably not within the threshold range. Moreover, the SVM does not exploit the contextual 18 information. Although only a few initial training samples were used, the PM effectively absorbs the 19 abundant and informative unlabeled samples to add to the training set by the AL, which makes it 20 outperform the detection performance compared with the SVM.

3.3 Compared with the PS³VM-D and CS⁴VM 21

22 Considering the DATA2 and DATA3, the performance of the PS³VM-D, CS⁴VM and PM is compared.

23 Fig. 10 and Fig. 11 show the detection grayscales of the three algorithms.



Fig. 10 Detection grayscales achieved on $DATA_2$ in terms of (a) CS^4VM , (b) PS^3VM -D and (c) PM.A represents the changed

areas, B represents the unchanged areas



Fig. 11 Detection grayscales achieved on DATA₃ in terms of (a) CS⁴VM, (b) PS³VM-D and (c) PM.A represents the changed

areas, B represents the unchanged areas

Through the threshold processing, the detection maps of DATA2 and DATA3are obtained, as shown in

- Fig. 12 and Fig. 13 respectively, where the white area is detected with the changes and the black area is
- detected as unchanged; A represents the changed areas and B represents the unchanged areas.







(c)

with the changes and the black area is detected as unchanged; A represents the changed areas and the B represents the unchanged areas



Fig. 13 Detection maps achieved on DATA₃ in terms of (a) CS⁴VM, (b) PS³VM-D and (c) PM, where the white area is detected

1 with the changes and the black area is detected as unchanged; A represents the changed areas and the B represents the unchanged 2 areas

3 In Fig. 12, the omission of PS³VM-D is the least and that of the PM is the greatest in A; the false alarm of PM is the least and that of the CS⁴VMisthegreatest in B. It can be seen that the performance of the 4 5 three algorithms is ideal and that of PM is more accurate than others for DATA₂. In Fig.13, the false 6 alarm of PM is significantly less than that of the other algorithms in B, followed by thePS³VM-D. The 7 omission of three algorithms is almost the same in A. Therefore, the detection result of PM is the best 8 for DATA₃.

9 In order to know the stability of the three algorithms, 6 different experiments were implemented for the

10 CS⁴VM, PS³VM-D and PM, respectively with the same initial training sets to obtain the results in

11 terms of OA and Kappa. The line charts of different results are drawn from small to large for



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18 Fig. 15 Line charts of CS⁴VM, PS³VM-D and PM achieved on DATA₃ in terms of (a) OA and (b) Kappa

19 For DATA₂ and DATA₃, except that the maximum of the OA and Kappa are basically the same for the 20 three algorithms, the rest of PM are significantly higher than those of thePS³VM-D and CS⁴VM. For 21 different initial sets, the change range of OA and Kappa for PS³VM-D and CS⁴VM is great and that for 22 PM is small. Therefore, the detection accuracy and stability of the PM are higher than other algorithms. 23 DATA₃is selected to illustrate the convergence of the CS⁴VM, PS³VM-D and PM. The curve of OA is 24 plotted in Fig. 16, where the X axis represents the number of iterations and the Y axis represents OA.



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2 Fig. 16 Line charts of PM achieved on DATA₃

3 With the increase of iterations, the OAs of the three algorithms all change, where the OA of the CS⁴VM

increases from 0.64 to 0.79, the OA of thePS³VM-D increases from 0.64 to 0.82 and the OA of PM 4

increases from 0.64 to 0.94. The curve of the PM rises fastest, which suggests that the PM can get the 5

6 faster convergence speed than other algorithms.

7 The CS⁴VM can increase the relevance of the training samples by searching the contextual samples, 8 but it does not consider whether those samples are beneficial to improve the convergence rate. The 9 PS³VM-D guarantees the information of the selected samples by searching them within the margin 10 band, but the probability that these samples are polluted is also great. Compared to the CS⁴VM and the 11 PS³VM-D, the PM uses the AL to select the informative samples, then use the context information to 12 increase the samples correlation, which improves the detection accuracy and ensures the reliability of 13 the selected samples. We use a new query function Q to make the distribution of the training samples 14 more uniform for improving the detection efficiency and accuracy. Moreover, the convergence of the 15 PM is further improved by applying the semilabeled samples.

16 3.4Fusion for PM

17 To obtain the more accurate results and verify the effectiveness of the fusion for the SSL methods, the 18 experimental results of the PM are fused. The OA and Kappa are listed in Table 1, and the fusion 19 detection maps are shown in Fig. 17, where the white area is detected with the changes and the black

20 area is detected as unchanged. A represents the changed areas and B represents the unchanged areas.



21 22

23 Fig. 17 Fusion detection maps achieved on (a) DATA₁, (b) DATA2 and (c) DATA3 for PM, where the white area is detected with 24 the changes and the black area is detected as unchanged; A represents the changed areas and the B represents the unchanged areas 25

Table 1OA and Kappa of different experiments for DATA1, DATA2 and DATA3

	1		1 2 3		4		5		6		Fusion			
	OA	Kappa												
DATA1	0.9718	0.8955	0.9662	0.8839	0.9668	0.8760	0.9717	0.8997	0.9413	0.8045	0.9724	0.8977	0.9744	0.9060
DATA2	0.9659	0.8582	0.9721	0.8661	0.9835	0.9225	0.9800	0.9053	0.9670	0.8365	0.9744	0.8894	0.9837	0.9250
DATA3	0.9475	0.6155	0.9420	0.6139	0.9409	0.6447	0.9451	0.5991	0.9072	0.5031	0.9528	0.6599	0.9534	0.6638

In TABEL 1, both the OA and Kappa get higher after fusion. By comparing Fig. 17(a), Fig. 17(b) and Fig. 17(c) with Fig. 8(b), Fig. 12(c) and Fig. 13(c) respectively, it is found that the false alarm in B and the omission in A reduces a lot after the fusion for **DATA**₁ and **DATA**₃. The false alarm in B region and the omission in A decreases slightly for **DATA**₂. Obviously, the data fusion could effectively compensate the detection error, reduce the risk caused by the different initial training sets and improve

6 the detection accuracy.

7 **4. Conclusion**

8 In this paper, a novel method is proposed for the change detection of RS images. It fully incorporates

9 the methods and concepts in the SSL, and adopts them to fit the situation where the labeled samples are

10 insufficient.

The novelty of this paper lies in: a) By considering the advantages of the AL and the context information, a novel semisupervised method is designed; b) by analyzing the distribution of the samples, a new query function is designed to select the semilabeled samples using the Euclidean distance; c) Based on the idea of data fusion, the discrete results of the PM are effectively fused. In the experiments of change detection for actual RSIs, the PM has made a significant improvement in the detection accuracy, convergence rate, and the stability in comparison with other existing methods. It can be further improved by using other effective fusion methods.

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4 5



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