[13] Development of the directed textural features automatic adjustment in the biomedical image analysis problems

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Abstract

As a part of the general problem of automatic information feature construction, we considered the particular applied problem of the calculation direction adjustment for the directed texture features designed to further diagnosis of various diseases by the digital biomedical images. As feature space quality criteria we considered the classification accuracy, Bhattacharyya distance and the discriminant analysis criteria. We used random search, genetic algorithm and simulated annealing as the optimization algorithms. Proposed approach reduces error probability estimation twice for the bone tissue X-ray images diagnosis problem (from 0.20 to 0.10), and also for lungs CT images diagnosis problem – by 45 % (from 0.11 to 0.06) in comparison with using of the conventional procedures for the selection of a large number of the heterogeneous features.

Keywords: textural analysis, feature construction, discriminant analysis, genetic algorithm, simulated annealing.

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Introduction

Texture analysis is an important tool in solving the tasks of diagnosing a variety of diseases on the base of digital images of biological tissues. Mathematical methods of its use for that purpose are described in detail in various monographs such as [1] and [2]. A common approach to the particular problem is the choice of large number of suitable textural features, classification algorithm selection and subsequent adjustment of the obtained recognition system, consisting in choosing parameters of features and algorithms and in selection of a small number of the most effective features. In most cases, both set up and feature selection are made manually using heuristic methods in a series of computational experiments.

There are attempts to automatize feature selection procedure, based on the feature space quality criteria. One such simple procedure of consistent inclusion of features such as described in [3], has already shown itself at its best in three applied problems: osteoporosis diagnosis based on X-ray images of the femoral neck [4], nephritic diseases diagnosis on digital imaging of ultrasound examination of kidneys [5], and diagnosis of chronic obstructive pulmonary disease (COPD) on computed tomography images [6]. This procedure allows to select from a large number of heterogeneous information signs a small group of signs, quasi-optimal by the criterion of discriminant analysis.

However, for feature selection one must first set from whatever reasons a variety of features from which selection would be made. If the features comprise parameters, then usually instead of one feature a whole family of features is being examined with different parameter values. The question remains open about methods of building new features from scratch, as well as about the setting methods for parametric features, especially if parameter values can be chosen from an infinite set.

These problems largely concern optimization and are often resolved by general optimization techniques designed for arbitrary functions. Mostly the genetic algorithm [7, 8] is used or the algorithm of simulated annealing [9]. Here, different criteria of quality of feature space or recognition systems as a whole are used as the target functions. However, usually it is about construction of new features as a certain kind of transformations of some set of primitive features, as was done in [7] and [8], or of local linear signs, as in [9].

In this paper we propose a general problem of constructing features and examine one of practically important examples of use of the proposed approach for automatic adjustment of the direction of calculation of directed textural features. The effectiveness of features adjustment method is verified experimentally on three sets of real diagnostic images. The main purpose of this work is to develop an effective method of automatic adjustment of calculating the direction of texture features, which allows to increase the accuracy of classification, compared with the usual procedure of selection from a large number of heterogeneous features.

1. Formulation of the task of building features

Suppose we have a set of objects of recognition Ω, broken up into L classes $\Delta=\{\Omega_l\}_{l=1,2,\dots,L}$, and a training set $U \subseteq \dot{\mathbf{U}}$, for objects of which we know their class in advance. Let us denote as $\Phi(\omega):\Omega\to\Delta$ a perfect detection operator that displays the object $\omega\in\dot{\mathbf{U}}_l$ in its class Ω_l. To solve the problem of recognition means to construct an operator $\Phi(\omega):\Omega\to\Delta$, which is engaged in the same, but wherein uses limited information about the objects of recognition.

Since the space Ω is not metric in most cases (e.g. if Ω is a plurality of digital images), the recognition operator $\tilde{\Phi}(\omega)$ is built as a superposition of two operators

$\tilde{\Phi}(\omega)=\mathrm{C}(\Psi(\omega))$,

where $\Psi(\omega):\Omega\to\Xi$ measures the information features of the object and transmits the detected object $\omega\in\Omega$ into its vector of features $x\in\Xi$, and $\mathrm{C}(x):\Xi\to\Delta$ is called *a classifier* and transmits a feature vector into a class of its prototype. The space Ξ is called *feature space.*

The task of feature construction is in choosing features calculation operator $\Psi(\omega):\Omega\to\Xi$, which provides the optimum of some quality criterion of a feature space $J(\Psi)$. To estimate the criteria value we can use the training set U.

In practice selection of an operator of features construction is always carried out from some set of admissible operators ψ. If the elements of function space ψ are heterogeneous and do not meet any properties, then the only way to implement selection of the best of them is to sort out them all, and for each to calculate a quality criterion.Evidently, if the space ψ contains infinitely many elements, it cannot be done.

Let then the space ψ contains a finite set of parametric families of operators, the elements of each of which are different in some parameter values. Since the families of operators still need to be sorted out, we can assume without loss of generality that ψ generally contains only one family of characteristics calculation operators $\psi(\omega,\theta):\Omega\times\Theta\to\Xi$, where Θ is a set of admissible values of the parameters, each of which is defined by a calculating features operator. Now the task of building features is in selection of a parameter $\hat{\theta}\in\Theta$, which provides maximum of some quality criterion of a feature space $J(\Psi,U)$, which is calculated according to the operator and the training set:

$$\hat{\Psi}(\omega)=\Psi\left(\omega,\arg\max_{\theta\in\Theta} J(\Psi(\omega,\theta),U)\right). \qquad (1)$$

Quality criterion $\mathcal{J}(\Psi,U)$ should be chosen so as to be able to quickly and accurately solve the optimization task. Since with the fixed training set and fixed operators family of features calculating $\Psi(\omega,\theta)$ the criterion $J(\Psi,U)$ depends only from θ, then it is possible for convenience to jot down $J(\theta)=J(\Psi(\omega,\theta),U)$.

In this formulation the task of features construction turns into an ordinary optimization problem which is solved with the use of appropriate methods of optimization. Depending on the characteristics of the operator $J(\theta)$ and a multitude of parameters Θ for its solution shall be chosen one of the suitable methods of optimization. Unfortunately, mainly there is no information about the function $J(\theta)$ character, so it is necessary to use the most common largely heuristic optimization techniques, such as various Monte Carlo methods [10], pseudo-gradient algorithm [11], evolutionary algorithms [12], simulated annealing [13].

2. The method of automatic adjustment of directed textural features

One of the simplest parameters of textural features is direction. Although histogram features based on moments are invariant to shifts and turns, most other characteristics such as correlation features, Haralika features, and features based on the lengths of the series vary depending on the direction. All these features depend on a certain coordinate shift (m,n), which means a shift to a direction $\sqrt{m^2+n^2}$ towards $\mathrm{arctg}(n/m)$. In the works [4-6] selection is made of the four families of features in horizontal, vertical, and two diagonal directions, but it is possible that a better quality of recognition could be achieved in a certain intermediate direction.

For the sake of universality of the method, in order not to change the method of calculating the features, we will not change the direction for the feature, but the rotation angle of the image, while the features will always be calculated in the horizontal direction. So for all images $\omega(m,n)$ we will make one and the same rotation transform

$$\begin{pmatrix} m' \\ n' \end{pmatrix} = A_\theta \begin{pmatrix} m \\ n \end{pmatrix},$$

where A_θ is the Givens matrix that turns the coordinate system by the angle θ:

$$A_\theta = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}.$$

Since for features listed the opposite directions do not differ then the variety of possible directions from which we are to choose the best is $\Theta = [0;\pi]$. It is demanded to choose from all angles $\theta \in [0;\pi]$ the $\hat{\theta}$ angle, which provides a maximum of some quality criterion of feature space $J(\theta)$. A certain optimization procedure will be needed for this . Choosing from different criteria $J(\theta)$ and different algorithms to optimize them, one can get different algorithms for automatic features tuning.

Quality criteria of feature space

Let us denote
$U_l^{'} = \{\Psi(\omega) \mid \omega \in U \cap \Omega_l\}$ –
feature vectors from the training set belonging to the class Ω_l, $U = \{\Psi(\omega) \ \omega \in U\}$ –
all feature vectors from the training set. In the work we investigated and compared the following quality criteria of feature space.

1. The proportion of correctly recognized objects

$$\tilde{J}(\theta) = \frac{1}{|U|}\left|\{\omega \in U \mid \Phi(\omega) = \tilde{\Phi}(\omega)\}\right| \qquad (2)$$

Hereinafter in the work for final sets the operator $|\bullet|$ returns the number of elements in the set. To effectively use a relatively small training set for calculation of this criterion, it is proposed to use *the elimination method of one object* [14]. It involves carrying out $|U|$ steps of training and classification, in each of which next one of the objects belonging to it is excluded from the training sample U, training is led only on remaining objects, and the expelled object is used as a recognition object. For classification, as well as everywhere in the work, we used the nearest neighbor algorithm.

2. Bhattacharyya distance [14]

$$\mu_{1/2} = \frac{1}{8}(a_1 - a_2)^T \left(\frac{R_1 + R_2}{2}\right)^{-1} (a_1 - a_2) +$$

$$+\frac{1}{2}\ln\left(\frac{1}{2}\frac{|R_1 + R_2|}{\sqrt{|R_1||R_2|}}\right), \text{where } a_l = \frac{1}{|U_l^{'}|}\sum_{x \in U_l^{'}} x$$

is assessment of intraclass mathematical expectation,

$$R_l(m,n) = \frac{1}{|U_l^{'}|}\sum_{x \in U_l^{'}} \left(x(m) - a_l(m)\right)\left(x(n) - a_l(n)\right)$$

is assessment of intraclass correlation matrix.

3. The first criterion of discriminant analysis

$J_1 = \mathrm{tr}\left(R_\Sigma^{-1} R_0\right)$, where $R_\Sigma = \frac{1}{L}\sum_{l=1}^{L} R_l$ –
is a matrix of an average intraclass scattering.

4. The second criterion of discriminant analysis

$$J_2 = \ln\left|R_\Sigma^{-1} R_0\right|. \qquad (3)$$

5. The fourth criterion of discriminant analysis

$$J_4 = \mathrm{tr}^{-1}(R_\Sigma)\,\mathrm{tr}(R_0). \qquad (4)$$

6. One more criterion of discriminant analysis from the work [15] $J_{SNR} = \dfrac{\|a_1 - a_2\|}{\mathrm{tr}(R_1) + \mathrm{tr}(R_2)}$.
In practice, the Euclidean norm was used to calculate this criterion. All discriminant analysis criteria are described in [14]. It was decided not to use the citerion J_3 described also there, as the choice of parameter there is a separate problem.

Optimization algorithms

Given the complexity of features calculation formulas depending on the rotation angle of the image it does not seem possible to reveal the direct relationship between the values of criteria of optimality $J(\theta)$ and the angle of rotation. Also, there are no grounds to assert the convexity or the unimodality of these criteria by angle of rotation. Therefore, to solve the optimization problem (1) we can only use common enough methods of stochastic optimization.

1. Method of random search.Let us take N_{opt} of random points $\{\theta_j\}_{j=1}^{N_{opt}}$, uniformly distributed on the segment $[0;\pi]$, then calculate the values $\{J(\theta_j)\}_{j=1}^{N_{opt}}$ and choose the maximal one.

2. Genetic algorithm. At the beginning of the algorithm work the initial points population is being generated $\{\theta_j\}_{j=1}^{N_{pop}}$. This can be done, for example, randomly, using the previous algorithm. Next, each step of the algorithm comes through three stages: mating, mutation, and selection [12].

Crossover operator $c(\theta_1, \theta_2)$ must get one point out of the two which will combine their properties. In the one-dimensional case, we can set it as a random value, in some way distributed on the interval $(\min\{\theta_1,\theta_2\}; \max\{\theta_1,\theta_2\})$.
At the stage of crossing from the old population are selected N_{pop} of different pairs of points $\{(\theta_1(j), \theta_2(j))\}_{j=1}^{N_{pop}}$ and a new population is formed $\{c(\theta_1(j), \theta_2(j))\}_{j=1}^{N_{pop}}$.
At the stage of mutation p_{mut} from all the points are subject to mutation by mutation operator. For example, we can select $\zeta(\theta)$ as the value of the random variable $\hat{\theta}$, distributed in a Gaussian law with mathematical expectation θ and dispersion $\pi^2/36$ (the rule of three sigma). If the value $\hat{\theta}$ does not lie in the segment $[0;\pi]$, then as a value $\zeta(\theta)$ we select such an angle $\theta_{mut} \in [0;\pi]$, that there is $k \in \mathbb{Z}$, such that $\theta_{mut} = \hat{\theta} + \pi k$.
At the last stage of the next step the selection occurs. Among all the points of the old and the new population there are left only those N_{pop} pieces for which the objective function $J(\theta)$ is maximum. They are used as the aged population in the next step. The algorithm stops when the function $J(\theta)$ has been computed already for N_{opt} points. After that from the points of the last population point $\hat{\theta}$ is selected, in which the target function $J(\theta)$ is maximum.

3. Simulated annealing algorithm [13] is char-

acterized by the initial temperature t_0, the temperature decreasing sequence t_0, $\{t_k\}_{k=1}^{\infty}$, as well as the operator, changing the current point $\zeta(\theta)$, e.g. such as the mutation operator of the genetic algorithm. The sequence of temperatures must be infinitely small, so, for example, a harmonic series $t_k = t_0 / k$ is suitable.

The algorithm itself contains a certain current point θ_{curr}, which initially can be chosen at random, e.g. $\theta_{curr} = 0$. At k-step a new point $\theta_{next} = \zeta(\theta_{curr})$ is considered. If $J(\theta_{curr}) < J(\theta_{next})$, then it is quite natural that at the next step it is supposed that $\theta_{curr} = \theta_{next}$. But if $J(\theta_{curr}) \geq J(\theta_{next})$, then at the next step all the same with probability

$$p_{sa} = \exp\left(-\frac{J(\theta_{curr}) - J(\theta_{next})}{t_k} \right)$$

it is supposed that $\theta_{curr} = \theta_{next}$, otherwise the current point will remain the same.

3. The results of computational experiments

Investigation of the quality of the described procedure of optimization of the direction of image rotation for improving the quality of its texture feature description was conducted in three experimental data sets.

1. X-ray femoral neck image obtained in clinics of Samara State Medical University in the study of patients with suspected osteoporosis. Examples of such images are given in [4]. Total images – 95. The average size of images – 1040 × 860.
2. Ultrasound images of the kidneys, obtained in the clinics of the Samara State Medical University in nephrology research. Examples of such images are given in [5]. Total images – 84. The average size of the image – 640 × 480.
3. The two-dimensional slices of X-ray images of computed tomography of lungs, obtained in the clinics of the Samara State Medical University. Examples of such images are given in [6]. Total number of images – 160. The average size of the image – 140 × 200.

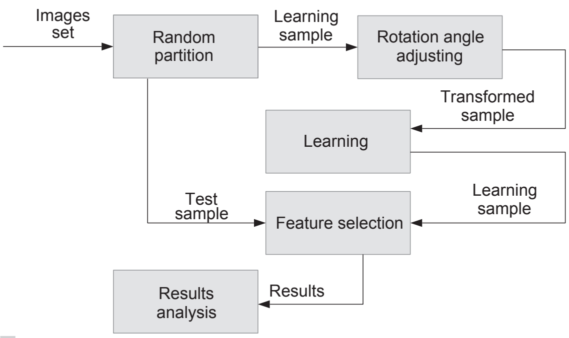

Fig. 1. Scheme of the experimental studies

All sets of images were randomly divided into two selections of the same volume: a training and a control one (from 95 images of bone tissue 47 were placed in the training set and 48 in the control one). After that for various combinations of quality criteria and optimization algorithms the rotation angle of image was adjusted, and as a result for obtained optimal angle feature values became also calculated. Then the values of features were also calculated for the control sample, and classification quality testing was made of obtained vectors of features by the criterion (2). Here for selection of an effective group of features a procedure was used based on the discriminant analysis criteria (4), like it was done in works [4-6]. Transparent scheme of experimental studies, conducted for each data set separately, is shown in Figure 1.

The following information features were used as directed:

1. The values of the co-variant function after 1 and 5 counts, as they were found to be most effective for the detection of X-ray images in the femoral neck in [4].
2. Haralik signs based on the entries matrices, as they were found to be most effective for detecting ultrasound images of the working kidneys [5].
3. Signs on the basis of the lengths of the series, as they were found to be most effective for computer tomography image recognition in working lungs [6].

As for calculating the features was used only the horizontal direction, the total number of unique features made up 40 pieces.

As the parameters of optimization algorithms was chosen the number of iterations $N_{opt} = 20$, the size of the population of the genetic algorithm $N_{pop} = 5$, the likelihood of a genetic mutation $p_{mut} = 0{,}1$, the initial temperature of the simulated annealing $t_0 = 10$. As a classification algorithm the method of the nearest neighbor was used, but the distance between the feature vectors was calculated by standardized features, normalized to the dispersion. Justification of the last was given in work [6].

Table 1. Research results of the features automatic adjusting for the femur x-ray images recognition problem

Optimization algorithm	Best criterion	Error	Angle
Random search	J_{SNR}	0.10	2.62
Genetic algorithm	J_4	0.12	2.47
Simulated annealing	J_4	0.10	2.49

Table 1 shows the results of a series of experiments with x-ray images of the femoral neck. In order not to overload the article with the results for each combination of optimization algorithm and quality criterion of feature space, for each optimization algorithm just the best is given by estimating the probability of erroneous recognition criteria. In addition, assessment of the likelihood of misclassification is shown,

$$\varepsilon = \frac{1}{|\tilde{U}|}\left|\left\{\omega \in \tilde{U} \mid \Phi(\omega) = \tilde{\Phi}(\omega)\right\}\right|, \quad (5)$$

calculated from images of the control samples Ω, as well as the actual values of the optimum angles in radians. It is seen that the obtained error value is two times lower than in [5].

Table 2. Research results of the features automatic adjusting for the kidneys ultrasonic images recognition problem

Optimization algorithm	Best criterion	Error	Angle
Random search	J_2	0.16	0.0
Genetic algorithm	J_2	0.16	0.0
Simulated annealing	J_2	0.16	0.0

Similarly, Table 2 shows the same data for image recognition tasks of kidney ultrasound. The resulting erroneous recognition score significantly higher than the value obtained in [5]. This is due to the fact that for technical reasons, the experiments were conducted on another set of data, for which the approach described in [5] also gives a similar error value. Furthermore, it is seen that the optimum value was zero angle, so that rotation of kidney image did not increase the quality of their recognition.

Table 3. Research results of the features automatic adjusting for the lungs CT images recognition problem

Optimization algorithm	Best criterion	Error	Angle
Random search	J_1	0.07	0.95
Genetic algorithm	$\tilde{J}$	0.07	2.18
Simulated annealing	J_2	0.06	1.75

Finally, Table 3 shows the results of experiments with lung computed tomography images. The resulting estimation of the probability of misclassification (5) is lower than in [6] and [16]. However, as in the previous tasks, no significant advantages of using any optimization algorithm is observed.

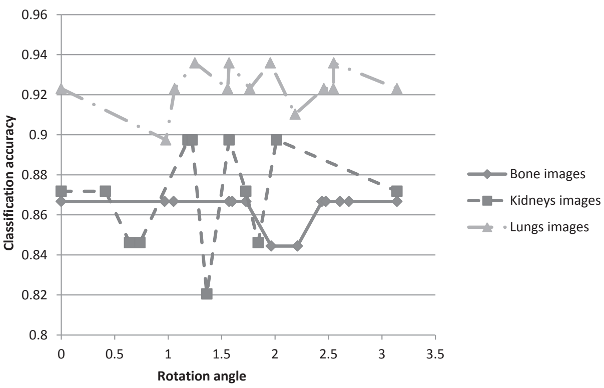

Fig.2. The dependence of classification reliability from image rotation angle in radians

Figure 2 shows graphs of the dependence of reliability of classification (2), calculated by the training sample by the method of elimination of an object, from the angle of rotation of the image in radians. Rotation angle values in the graphs were selected during the simulated annealing algorithm. It is noticeable that for the ultrasound images of the kidneys the accuracy of the classification changes rather chaotically, while for the X-ray image of the femoral neck and for computed tomography imaging of lungs the dependence looks smooth. For them, some ranges of angles are better than others.

On the average for all three tasks random search algorithm provides an estimate of the probability of misclassification of 0.122 at an average rate of 16.5 of effective group of features, genetic algorithm – an error of 0.123 on average at 17.4 features, and simulated annealing – error 0.120 on average at 20, 7 features. Among the quality criteria of feature space in average the most effective of all the tasks is the criterion (3). It provides an average estimate of the probability of misclassification 0,118 at an average rate of effective features group 15.44, which is slightly better than the same indicators in other quality criteria.

Finally we present the resulting estimates of probability of misclassification with confidence intervals Agresti-Cole [17], as was done in [6]. For images of bone tissue assessment of the likelihood of misclassification is 0,13 ± 0,08, for ultrasonic imaging of kidneys – 0,19 ± 0,11, and for computed tomography images of lungs – 0,08 ± 0,05. All values are given with the confidence level.

Conclusion

The paper sets a common goal of setting features, and basing on it provides a simple practically useful approach to automatic adjustment of direction for directed textural features. This approach was studied on three real problems of medical diagnosis of diseases on radiological images of biological tissues. The result of experiments shows the advantages of using this approach, and most effective optimization algorithms and feature space quality criteria are found for this task .

Using the automatic adjustment of directed textural features reduces probability asssesment of erroneous recognition to diagnose the problem of X-ray images of bone tissue in half (from 0.20 o 0.10). Besides, for the task of diagnostics of computed tomography images of lungs the error is reduced by 45% (from 0.11 to 0.06) as compared to conventional procedures of selection from a large number of diverse characteristics. This indicates the practical suitability of the proposed approach for solving the tasks of texture analysis of biomedical images.

The experiments also proved that the use of sophisticated optimization algorithms such as genetic algorithm and simulated annealing algorithm does not provide significant advantages as compared with a simple method of random search. Nevertheless, we can recommend to use in practice the simulated annealing algorithm, as it provides a 2.4% average less value of detection error than the other two algorithms.

Unfortunately, a single most effective criteria of feature space quality cannot be seen. In practice one could probably recommend the use of discriminant analysis criterion (3), because it provides an average of slightly better error recognition performance, although in fact combined criteria should be developed or multi-criteria optimization should be used [18].

Also, in the future we need to further explore a new set of images of kidneys ultrasound data, because it demonstrated the lack of repeatability of the results obtained in [5]. This is probably due to low quality of the new set of data, as well as the fact that there different images were obtained at different ultrasound devices with different settings.

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