# Algorithm of Particle Filtering of Recognition in Visual Aided Navigation

**M.P. MUKHINA, I.V. SEDEN, M.F. TUPITSYN, A.S. YURCHENKO**

***Abstract*** **–** The particle filtering algorithm is developed to increase the accuracy of extreme Bayesian recognition. The unified meta template (image of ground surface) is represented in the form of SURF descriptor form. Template class probabilities are determined by introducing the normalized correlation coefficient as weight of particle (feature point) in each class. Quality of recognition over template classes in simulations has been up to 90% with believable transition probabilities between classes.

***Index Terms*** **–** visual aided navigation, specific features and attributes of image, speed-up robust feature.

## I. INTRODUCTION

Visual aided navigation is one of promising variants of alternative to satellite navigation, especially for unmanned aerial vehicles (UAV). Visual information can be used to compensate the error accumulation in inertial navigation systems (INS) and to increase the flight safety [1].

Visual aided navigation consists of two main parts. The first, absolute navigation, or georeferencing [2] mostly relies on recognition of current image frame among template satellite imaginary by feature and correlation approaches. The second, relative navigation, or visual odometry[3] takes a series of video frames and obtains the relative velocities from increments between them. Here also possible two approaches: feature tracking from frame to frame or correlation between consequence frames.

Both tasks of visual navigation, recognition and tracking, must be solved in real-time by processing large amount of video information. The image features are used to eliminate frame redundancy and recognition and tracking are possible to perform by combining statistical data processing and fusion algorithms in single algorithm of joint particle filtering [4].

## II. PREVIOUS WORK

The known problem statement of probability estimation was formulated in [5]. The approach of particle Bayesian filters is used in variety of applications: data analysis, radar tracking, terrain aided navigation, simultaneous localization and mapping (SLAM), growth model simulation, fault diagnosis, etc. Recent papers propose the use of joint particle filter for the recognition and tracking [4], [6], [7], [8].

In [4] the algorithm of joint particle filter has been proposed to provide kinematic tracking of target simultaneously with its classification. State vector combines both kinematic parameters of target and its features to describe its class. In particle filtering each class is represented by fixed number of particles and correspondingly resampling is done separately for each class.

In [6] the integration of a particle filter and a continuous version of the transferable belief model have been used. The output from the particle filter is used as input to the transferable belief model. The transferable belief model's continuous nature allows for the prior knowledge over the classification space to be incorporated within the system. Classification of objects demonstrates a morerobust results in comparison with classical Bayesian classification routine and the output is less influenced by noise.

In [7] a multiple model particle filter and a mixture Kalman filter have been designed for two-class identification. The results demonstrate the usefulness of the proposed scheme for the incorporation of additional speed information. Both filters illustrate the opportunity of the particle filtering and mixture Kalman filtering to incorporate constraints in a natural way, providing reliable tracking and correct classification. In the framework an algorithm for delayed estimation is designed for improving the current modal state estimate.

In [8] the methodology of joint particle filter has been demonstrated successfully on the tracking and identification of geometric shapes in video sequences. Combined techniques are used to estimate the shape features. The first technique is a resample-MCMC move that is applied to re-scale both the dimensions of the target and the whole trajectory. Then, a sufficient statisticssummarizes the whole trajectory so the computational and memory requirements of the re-scaling moves are reasonable. In order to be able to reach any point of the hyper-parameter space, other moves are needed. They consist in deformation moves that change the shape dimensions without keeping the proportions. Since no sufficient statistic is available, an artificial evolution is used consisting of a deformation diffusion through the layers.

A number of image descriptors have been developed for object recognition and image classification [9]. Perfect review of existing features and their descriptors is done in [10]. In visual navigation there are specific requirements to feature image representation to create unified template.

Specific features (Fig. 1) of image have the following kinds of attributes:

- Location: ends of intervals, center of gravity of region, tops of polygons:
- Geometrical attributes: orientation, length, curvature, area, perimeter, width of the line, minimum and



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maximum diameter of region, symmetry axis, number and location of special points, compactness ratio;

- Radiometric attributes: contrast, statistics of brightness distribution, sign and edge value, autocorrelation;
- Texture attributes: co-occurrence matrix, homogeneity index, energy, entropy, statistics of texture gradients, results of texture filters application, moments;
- Topology attributes: coherence, neighborhood, mutual points, cross over, parallelism, covering, integration;
- Color/polyzonal attributes: vector of attributes for every channel;
- Dynamic attributes: attributes of static and moveable objects;
- Time attributes: functions of attribute changes with time.

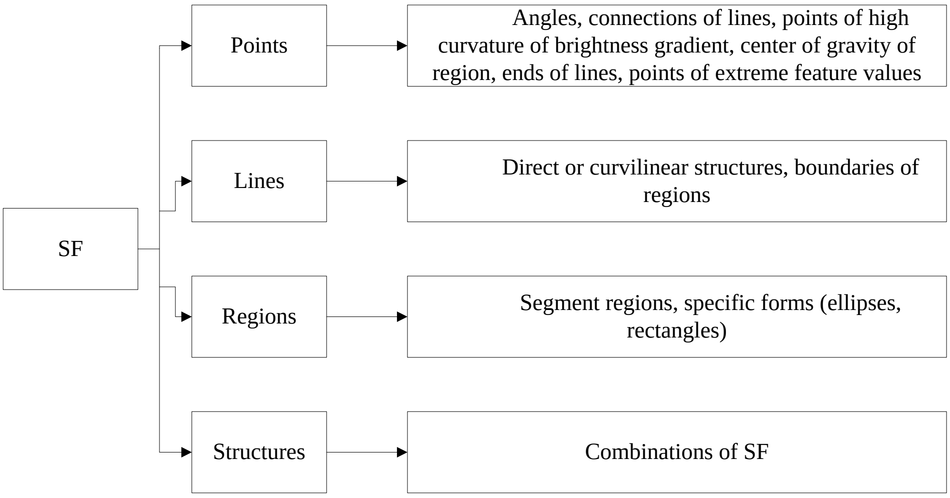


Fig. 1 Classification of specific features (SF)

Basic criteria of choice of definite specific features and their attributes for recognition algorithms are described in [11].

Reference template could be chosen at any part of region of meta image. Unsuccessful choice of template could significantly degrade the results of similarity measure.The task of choice of informative sections of images for reliable and accurate comparison of images does not have the final solution till now. The main problem lies in the choice of optimal composition of contradictory requirements of flexible and adaptive analysis of informativeness and fast algorithms of estimate calculation.

## III. PROBLEM STATEMENT

Recognition in visual navigation is assumed to be the process of determining the relation of current frame (image) to the corresponding reference template (map fragment) by analyzing the vector values of observed features.

A set of templates (reference image fragments) is denoted as $\mathbf{C} = \{C_i\}, i = 1,...,n$, where *n* is total number of templates. Each template contains a number of characteristic features $C_i = \{D_1, D_2, ..., D_{N_i}\}$. Accordingly, on the each current frame there is an observation (measurement) of a certain number of the characteristic features, inherent to this image, and thus, the measurement vector is formed as $\mathbf{z} = [D_1, D_2, ..., D_m]^T$.

Space of characteristic features $\mathfrak{R}^N$ contains the points, that related to one of the templates. Areas of templates (classes) ideally should be compact and uniquely separated from each other and attributed. Such groups of vector features of classes are called clusters. It is clear, that their compactness and isolation from each other allows us to use simple recognition schemes, such as classification of template by distance to gravity center of clusters or by the average distance to all elements of training sample [12].

However, in practice features variability of images is quite large, which leads to the intersection of clusters and relation of current frame to one or another templates becomes of probabilistic nature.

Therefore the problem of visual navigation is advisable to use methods and algorithms of extreme recognition based on a statistical approach to estimation. Also necessary to choose complex approach to formation of image informative features and to unification of template. Basic requirements for the characteristic features containthe unique description and their invariance to possible changes in the image.

During the observation of ground surface and formation of the current frame the measurement vector **z** with characteristic features is formed. Let's assume, that this observation vector is a random vector with a conditional probability density function (pdf), which depends on the affiliation of this vector with certain template.With recognition of the frame the problem formally is reduced to a hypothesis testing $H_1, H_2, ..., H_n$, where $H_i$ is hypothesis of belonging of the current frame to *i*-thtemplate. It is assumed that a prior distribution of hypotheses probabilities $p(H_i)$ are known. In this case $\sum_{i=1}^{k} p(H_i) = 1$, because the frame must belong to one of the templates.

The conditional pdf of frame **z** belonging to the template *Ci* is denoted as $p(H_i \mid \mathbf{z})$. If it is decided that the frame **z** belongs to the template $C_j$, when actually it belongs to the reference class $C_i$, then the losses or risk of false classifications is designated as $L_{ij}$. Since the frame can belong to any of these templates, then mathematical


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expectation of losses, associated with the assignment of the observed object to the template $C_j$, is determined by the following expression:

$$\pi_j(\mathbf{z}) = \sum_{i=1}^{n} L_{ij}\, p\left(H_i \mid \mathbf{z}\right) \quad ,$$

this value is called conditional average risk of classification

With recognition of each frame the classifier can relate it to one of $n$ possible templates. If for each frame $\mathbf{z}$ the values of the conditional mean of losses $\pi_1(\mathbf{z}), \pi_2(\mathbf{z}), ..., \pi_n(\mathbf{z})$ are calculated, and classifier refers the frame to the template, which corresponding to the smallest conditional losses, it is obvious that mathematical expectation of total losses on a set of all decisions will also be minimized. This classifier is called Bayesian classifier [13]. From a statistical point of view Bayesian classifier corresponds to optimal quality of classification.

## IV. Bayesian estimation

Known problem statement of optimal statistic estimation [5] is formulated as following: to find the estimate of state vector $\mathbf{x}_k \in \mathbf{R}^n$, where $n \in N$ is the dimension of vector given at a set of discrete time moments with indexes $k \in N$. The evaluation of state vector $\mathbf{x}_k$ in time is described by stochastic equation:

$$\mathbf{x}_k = f_k\left(\mathbf{x}_{k-1}, \xi_k\right), \quad (1)$$

where $f_k$ is known transition function, in general case non-linear, that depends on state vector $\mathbf{x}_{k-1}$ and random disturbance $\xi_k$. The state vector is observed and expressed by measurement equation as a random process $\mathbf{z}_k \in \mathbf{R}^m$

$$\mathbf{z}_k = h_k\left(\mathbf{x}_k, \zeta_k\right), \quad (2)$$

where $h_k$ is known and also non-linear function of state vector and random measurement noise $\zeta_k$. Statistical parameters of noise are assumed to be known.

If the noises are additive, then equations (1)-(2) can be represented as following:

$$\mathbf{x}_k = f_k\left(\mathbf{x}_{k-1}\right) + \xi_k,$$

$$\mathbf{z}_k = h_k\left(\mathbf{x}_k\right) + \zeta_k.$$

Also there is an assumption that process $\mathbf{x}_k$ is Markov process and can be described by transition pdf $p\left(\mathbf{x}_k \mid \mathbf{x}_{k-1}\right)$. The likelihood function can be described by pdf $p\left(\mathbf{z}_k \mid \mathbf{x}_k\right)$.

To solve the problem of optimal estimation it is necessary to get the conditional pdf $p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)$, where $\mathbf{Z}_k$ is all series of measurements till moment $k$, that is $\mathbf{Z}_k = \left\{\mathbf{z}_i\right\}_{i=1}^{k}$. If the pdf is known at moment $k$-1, then it is possible to extrapolate it by Kolmogorov- Chapman equations:

$$p\left(\mathbf{x}_k \mid \mathbf{Z}_{k-1}\right) = \int p\left(\mathbf{x}_k \mid \mathbf{x}_{k-1}\right) p\left(\mathbf{x}_{k-1} \mid \mathbf{Z}_{k-1}\right) d\mathbf{x}_{k-1}. \quad (3)$$

After new measurement $\mathbf{z}_k$ in moment $k$ the extrapolated pdf $p\left(\mathbf{x}_k \mid \mathbf{Z}_{k-1}\right)$ can be corrected by using well known Bayesian formula:

$$p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right) = p\left(\mathbf{x}_k \mid \mathbf{z}_k, \mathbf{Z}_{k-1}\right) = \frac{p\left(\mathbf{z}_k \mid \mathbf{x}_k, \mathbf{Z}_{k-1}\right) p\left(x_k \mid \mathbf{Z}_{k-1}\right)}{p\left(\mathbf{z}_k \mid \mathbf{Z}_{k-1}\right)} =$$

$$= \eta^{-1} \cdot p\left(\mathbf{z}_k \mid \mathbf{x}_k\right) p\left(x_k \mid \mathbf{Z}_{k-1}\right), \quad (4)$$

where value $\eta^{-1}$ is normalized constant

$$\eta^{-1} = p\left(\mathbf{z}_k \mid \mathbf{Z}_{k-1}\right) = \int p\left(\mathbf{z}_k \mid \mathbf{x}_k\right) p\left(\mathbf{x}_k \mid \mathbf{Z}_{k-1}\right) d\mathbf{x}_k,$$

that can be determined from the condition

$$\int p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right) d\mathbf{x}_k = 1.$$

If there is conditional pdf $p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)$, then it is possible to find the estimate of state vector $\hat{\mathbf{x}}_k$ according to the selected optimality criteria.

Thus, in general case, the problem of optimal estimation consists of two main stages: prediction-update, equations (3)-(4). But realization is complicated and possible only for a few cases. In general there is no closed-form expression for pdf $p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)$ due mainly to the unstructured non-linearity, and there is no solution that updates the conditional density analytically. The exception is the case of the linear state and measurement models with Gaussian noises. In this case the optimum estimator is the Kalman filter [14].

## V. State equation of object motion dynamics

General model of dynamics of object motion is linear motion in 2D space with varying $x$,$y$ coordinates, their derivatives and joint state component characterizing the template ID[15]. State vector is $\mathbf{x}_k = \left[x, \dot{x}, y, \dot{y}\right]^T$. The discrete-time system model is

$$\mathbf{x}_{k+1} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}_k + \xi_k,$$

where $\xi_k$ is an additive white Gaussian noise with covariance.

$$\mathbf{Q} = \begin{bmatrix} T^3/3 & T^2/2 & 0 & 0 \\ T^2/2 & T & 0 & 0 \\ 0 & 0 & T^3/3 & T^2/2 \\ 0 & 0 & T^2/2 & T \end{bmatrix} T\sigma^2.$$

Let's join to the state vector the additional component, characterizing the ID of template to which the current frame belongs: $\mathbf{s} \in \left\{s_i, i = 1, ..., m\right\}$. Then the join state vector contains two parts: kinematic state and feature-based correlated ID of template.

Measurements are available also in join form: $\mathbf{z}_t = \left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature} = \left[D_1, D_2, ..., D_M\right]^T\right\}_t$. It is assumed that a prior distribution of hypotheses probabilities $p\left(H_i\right)$ are known. The measurement is characterized by the conditional pdf

$$p\left(\left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\} \mid \left\{\mathbf{x}, \mathbf{s}\right\}\right) = h_{\{\mathbf{x},\mathbf{s}\}}\left(\left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\}\right)$$


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The measurement function $h_{\{\mathbf{x},\mathbf{s}\}}\left(\left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\}\right)$ is highly non-linear.

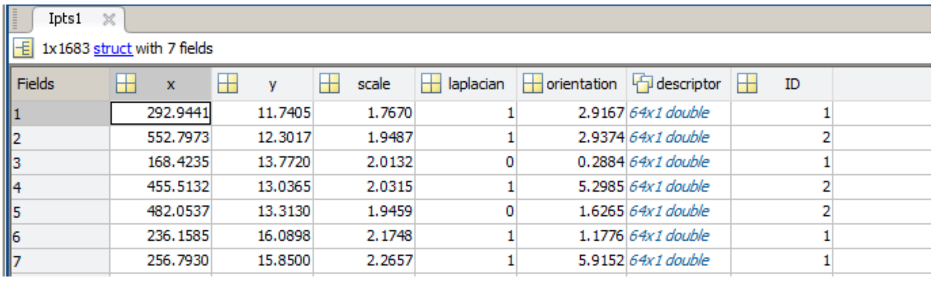
## VI. MEASUREMENT MODEL BY TEMPLATE SURF DESCRIPTOR

Let's now consider the equations (1) and (2) for the problem of visual navigation. The reference image is given in a descriptor representation of its characteristic features:

$$I = \{D_1, D_2, ..., D_N\},$$

where correspondingly $D_1$, ..., $D_N$ are descriptors of image characteristic features in $N$ number. The descriptors may contain not only a unique description of features, but also additional information needed to solve navigation problems.

The reference image is represented by feature points and their corresponding descriptors by Speed-Up Robust Feature (SURF) method [16]. Descriptor has the following data fields: coordinates $P = \{x, y\}$, scale of Gaussian filter $M = \{\sigma\}$, gradient orientation $R = \{\varphi\}$, Laplacian $L = \{0,1\}$ (means either white spot on black background or black spot on white), and gradients of quadrants, which surround the point (8 × 8 matrix), template ID (Fig. 2).



Ipts1
1x1683 struct with 7 fields

| Fields | x | y | scale | laplacian | orientation | descriptor | ID |
|---|---|---|---|---|---|---|---|
| 1 | 292.9441 | 11.7405 | 1.7670 | 1 | 2.9167 | 64x1 double | 1 |
| 2 | 552.7973 | 12.3017 | 1.9487 | 1 | 2.9374 | 64x1 double | 2 |
| 3 | 168.4235 | 13.7720 | 2.0132 | 0 | 0.2884 | 64x1 double | 1 |
| 4 | 455.5132 | 13.0365 | 2.0315 | 1 | 5.2985 | 64x1 double | 2 |
| 5 | 482.0537 | 13.3130 | 1.9459 | 0 | 1.6265 | 64x1 double | 2 |
| 6 | 236.1585 | 16.0898 | 2.1748 | 1 | 1.1776 | 64x1 double | 1 |
| 7 | 256.7930 | 15.8500 | 2.2657 | 1 | 5.9152 | 64x1 double | 1 |

Fig. 2 Data fields of SURF descriptor in Matlab

The normalized correlation function for descriptor matrices is of the following form:

$$K_{ij} = \frac{D_i(64) \cdot D_j(64)}{\sqrt{D_i^2(64) \cdot D_j^2(64)}}, \; i = 1...N, \; j = 1...M \quad (5)$$

where indexes $i$, $j$ correspond to the feature points on the template and current images, and respectively $N$, $M$ are numbers of found points on these images.

Realization of SURF method in (Code of SURF listing in MATLAB) was used in practice for experiments. The descriptors are formed as matrix **D** by size 64×$N$, where $N$ is number of feature points. The function (5) can be found by *single* multiplication of two matrixes of template and current image descriptors:

$$\mathbf{K} = \mathbf{D}_{template}^T \cdot \mathbf{D}_{current} = \begin{bmatrix} D_1(1) & \cdots & D_1(N) \\ \vdots & \ddots & \vdots \\ D_{64}(1) & \cdots & D_{64}(N) \end{bmatrix}^T \cdot \begin{bmatrix} D_1'(1) & \cdots & D_1'(M) \\ \vdots & \ddots & \vdots \\ D_{64}'(1) & \cdots & D_{64}'(M) \end{bmatrix}. \quad (6)$$

Since descriptor matrix is already normalized due to peculiarities of SURF method, then it is possible to state that each component $K_{ij}$ of matrix (6) corresponds to (5). Obviously, the maximal values in matrix **K** take for the best matches between feature points. Search of maximal elements is done by the finding the maximal values of matrix (9) in each row and checking whether this value is greater than the threshold. Only one maximal element in each row is selected since it is supposed that one point on the template will be matched to the single point on the current image.

Thus, the measurement vector can be represented as a set of characteristic features defined at the current time on a frame as $\mathbf{z}_{feature} = [D_1, D_2, ..., D_M]_t^T$, where $M$ is a number of features in the current frame.

## VII. PARTICLE FILTERING ALGORITHM

The basic idea of determination the template class probabilities is to assign the pre-determined number of particles with each class, depending on the number of SURF feature points: $N = N_1 + N_2 + ... + N_s$, where $N$ is a number of feature points on meta template, $N_1$,..., $N_s$ are corresponding numbers of points in templates. There are $s$ templates ($i$ = 1, ..., $s$) on meta template and $N_i$particles in each template ( $j = 1,..., N_i$ ). The weight of $k$-th particle in $i$-thtemplate is determined by the normalized correlation coefficient (NCC) determined by (5).Then the weights are normalized for each class to satisfy $\sum_{j=1}^{N_i} w_k^{i,j} = 1$.

Further, the algorithm is represented as following.

For each template $i$ = 1, ..., $s$

Draw particles $x_k^{i,j} \sim q\left(x_k \mid x_{k-1}^{i,j}, \left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\}, s_i\right)$ for $j = 1,..., N_i$.

Calculate weights

$$w_k^{i,j} = w_{k-1}^{i,j} \frac{p\left(\left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\} \mid x_k\right) p\left(x_k \mid x_{k-1}^{i,j}, s_i\right)}{q\left(x_k \mid x_{k-1}^{i,j}, \left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\}, s_i\right)}.$$

Calculate template class probability



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$$p\left(\left\{\mathbf{z}_{kinematic}, \mathbf{z}_{feature}\right\} \mid \left\{\mathbf{z}^{k-1}{}_{kinematic}, \mathbf{z}^{k-1}{}_{feature}\right\}, s_i\right) = \sum_{j}^{N_i} w_k^{i,j} \ .$$

Normalization of weights over *i*-th template:

$$w_k^{i,j} = \frac{w_k^{i,j}}{\sum_{j}^{N_i} w_k^{i,j}} .$$

End.

## VIII. Experimental results

Simulations were done on meta template of 600x800 px to be separated in 4 templates (Fig. 3) and pre-processed by SURF detector. The current frames were taken by cropping the original image of size 200x200 px starting with left upper corner of it.

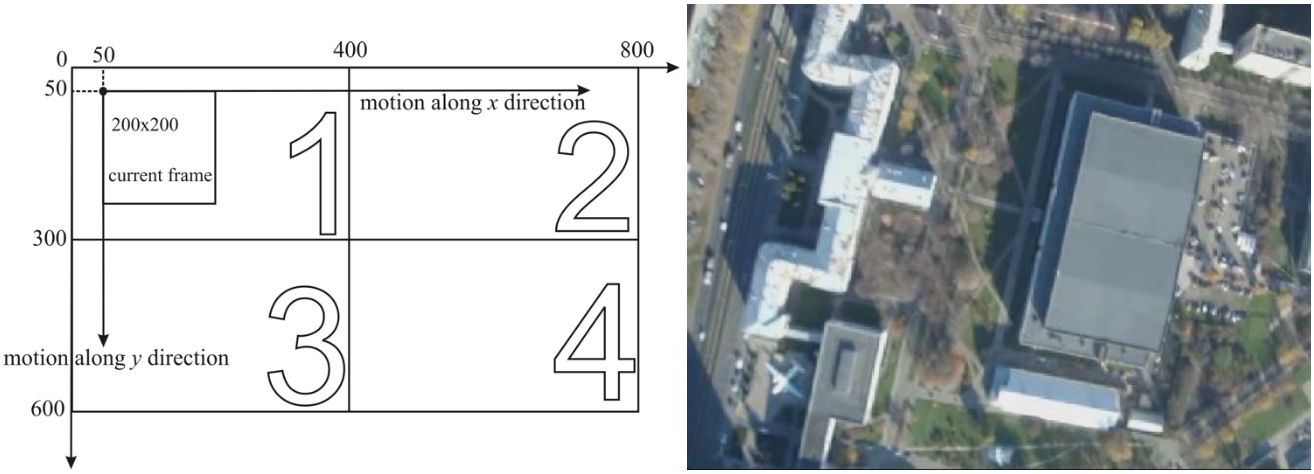


Fig. 3 Meta template with four templates and directions of current frame motion

Matlab script was running for three types of motion models: linear motion in *x* direction, linear motion in *y* direction and linear motion with constant rate over *x* and *y* directions. Results are presented in Fig. 4, Fig. 5 and Fig. 6.

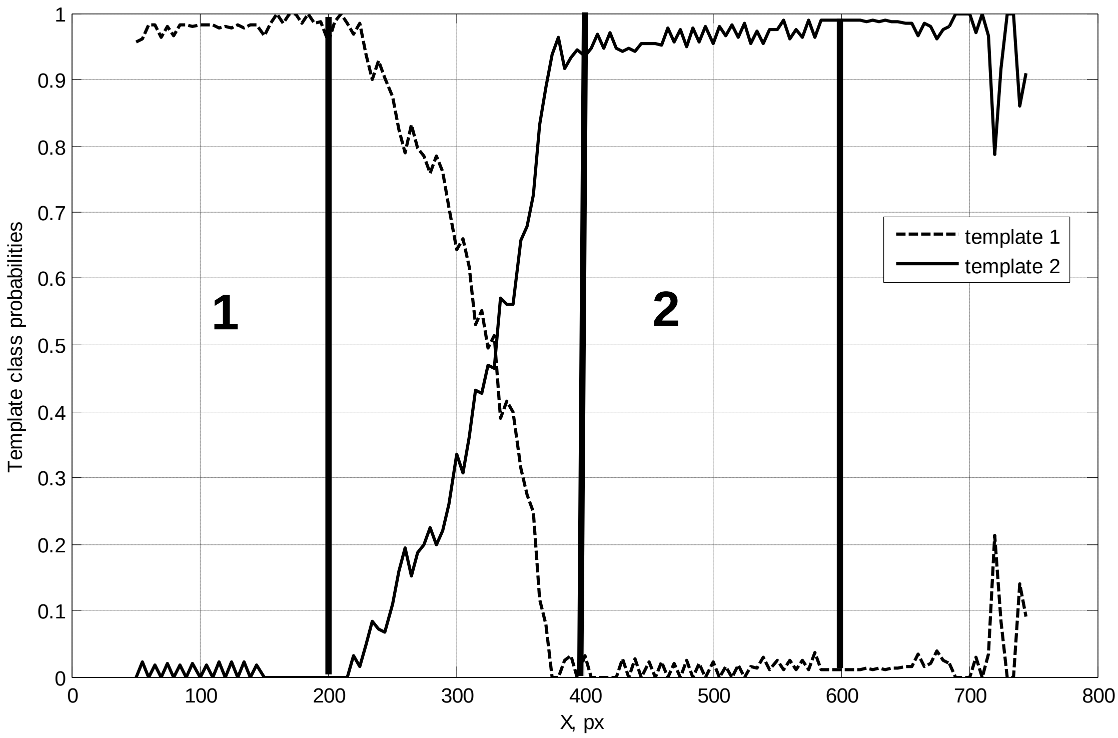


Fig. 4. Motion of frame 200×200 along *x* direction, starting with left upper corner point from 50 px to 745 px of unified template size 600×800. By bold lines the areas of 100% probability of belonging the current frame to a given template are separated. Other areas are current images with fragments from either several templates (between 1 and 2) or with lack of data.



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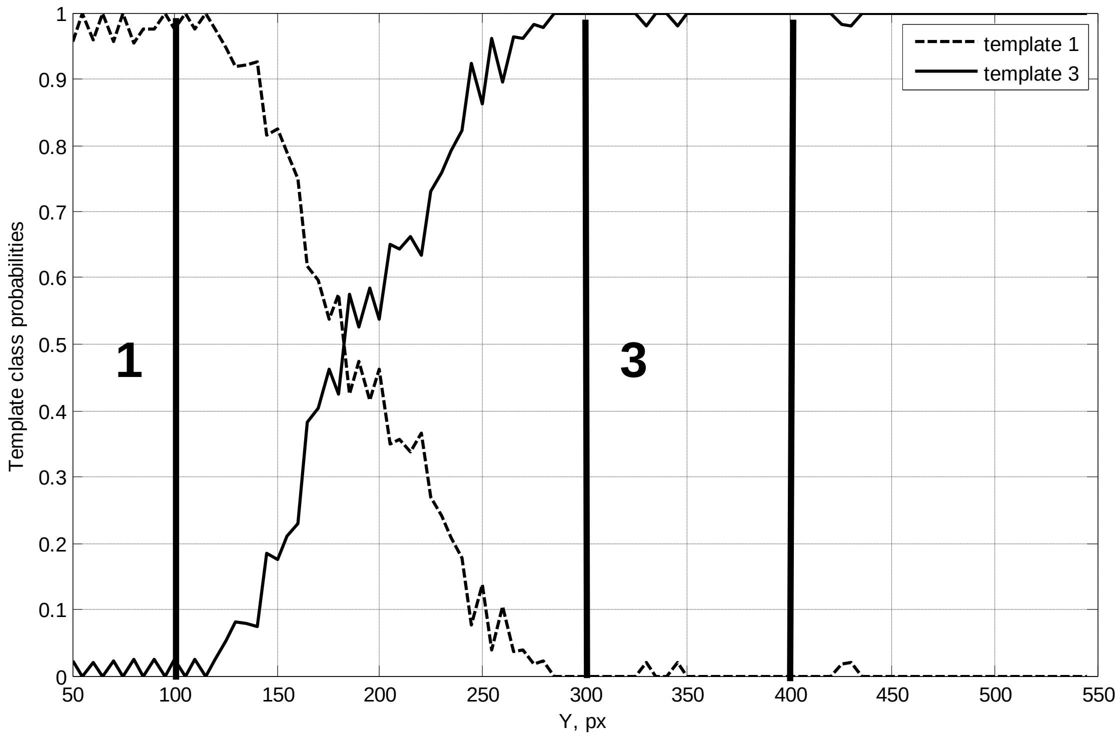


Fig. 5. Motion of frame 200×200 along *y* direction, starting with left upper corner point from 50 px to 545 px of unified template size 600×800. By bold lines the areas of 100% probability of belonging the current frame to a given template are separated. Other areas are current images with fragments from either several templates (between 1 and 3) or with lack of data.

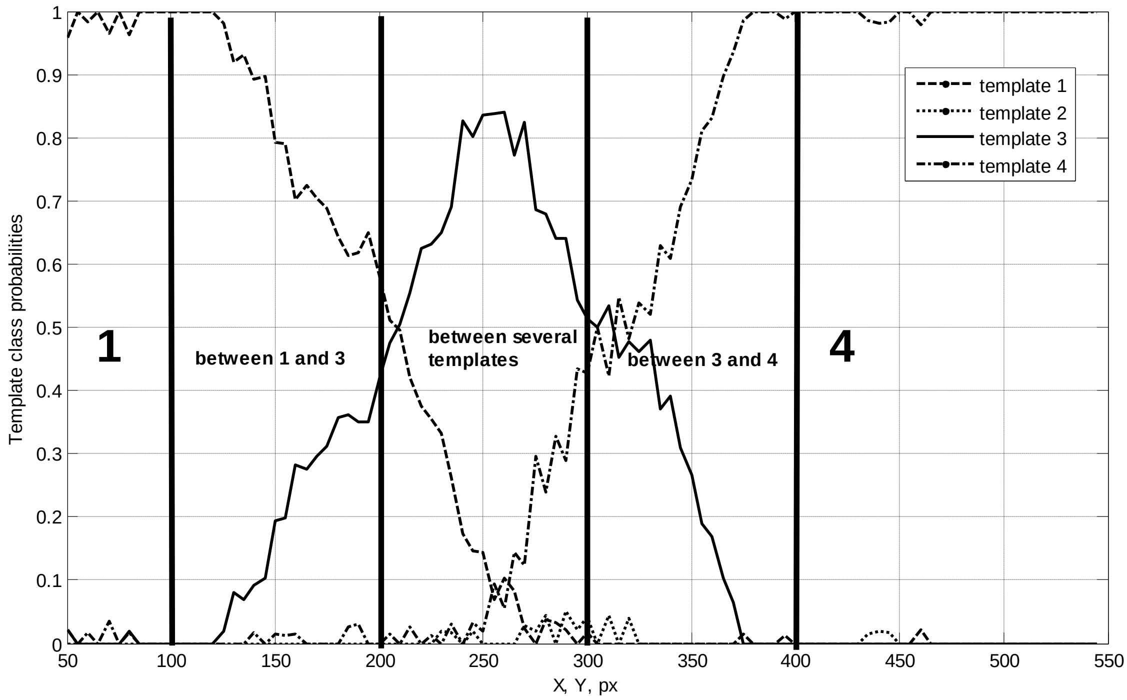


Fig. 6. Motion of frame 200×200 along *x*, *y* directions, starting with left upper corner point from 50 px to 545 px of unified template size 600×800. By bold lines the areas of 100% probability of belonging the current frame to a given template are separated. Other areas are current images with fragments from either several templates or with lack of data.

General number of feature points over meta template is 1702. In each template number of feature points is approximate of the same order: 469, 379, 404, 431. The quality of estimation depends on the number of feature points determined on the current frame. If the number is not



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reliable (less than given threshold) then the process of recognition will be erroneous.

Demonstration of this was done by selecting the frame size smaller than 10% from template size (40x40 px for presented in Fig. 3). In this case for some frame there was no feature point to be detected at all. By increasing size of current frame twice (80x80 px) the quality of recognition remains unsatisfied (Fig. 7), probabilities of templates are below 90%.

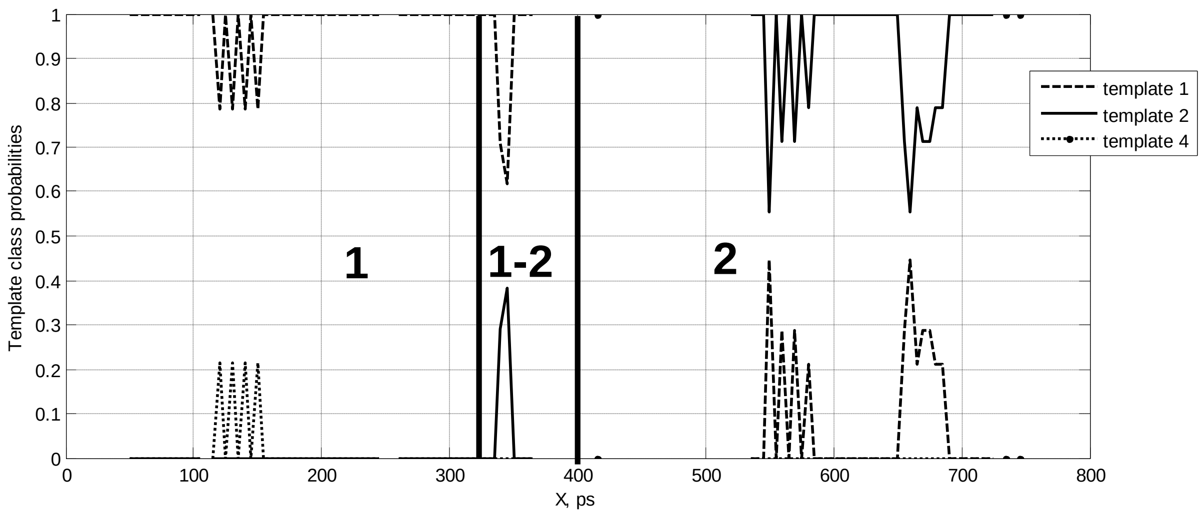


Fig. 7. Motion of frame 80×80 along *x* direction, starting with left upper corner point from 50 px to 745 px of unified template size 600×800. By bold lines the areas of 100% probability of belonging the current frame to a given template are separated. Other areas are current images with fragments from either several templates or with lack of data.

## IX. CONCLUSIONS

The particle filtering algorithm is developed to increase the accuracy of extreme Bayesian recognition. The unified meta template (image of ground surface) is represented in the form of SURF descriptor form to minimize the memory space with simultaneous saving the uniqueness and invariance of template. Template class probabilities are determined by introducing the normalized correlation coefficient as weight of particle (feature point) in each class. Number of particles in each class is fixed and pre-determined by number of feature points defined on meta template. Quality of recognition over template classes in simulations has been up to 90% with believable transition probabilities between classes.

## REFERENCES

[1] Lee K., Kriesel J. M., Gat N. Autonomous Airborne Video-Aided Navigation //Navigation. – 2010. – Т. 57. – №. 3. – С. 163-173.

[2] G. Conte and P. Doherty. An integrated UAV navigation system based on aerial image matching. In IEEE Aerospace Conference, Big Sky, Montana, March 2008.

[3] Dong-Gyu Sim, Rae-Hong Park, Rin-Chul Kim, Sang Uk Lee, Ihn-Cheol Kim "Integrated Position Estimation Using Aerial Image Sequences" //IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, No. 1, January 2002. – P. 1-18.

[4] Gordon N. J., Maskell S., Kirubarajan T. Efficient particle filters for joint tracking and classification //AeroSense 2002. – International Society for Optics and Photonics, 2002. – С. 439-449.

[5] Doucet A., Godsill S. and Andrieu C. On sequential Monte-Carlo isampling methods for Bayesian filtering // Statistics an Computing, vol. 10, no. 3, pp. 197-208, 2000

[6] Powell G. et al. Joint tracking and classification of airbourne objects using particle filters and the continuous transferable belief model //Information Fusion, 2006 9th International Conference on. – IEEE, 2006. – С. 1-8.

[7] Angelova D., Mihaylova L. Joint target tracking and classification with particle filtering and mixture Kalman filtering using kinematic radar information //Digital Signal Processing. – 2006. – Т. 16. – №. 2. – С. 180-204.

[8] Minvielle P. et al. A Bayesian approach to joint tracking and identification of geometric shapes in video sequences //Image and Vision Computing. – 2010. – Т. 28. – №. 1. – С. 111-123.

[9] A. Oliva and A. Torralba. Modeling the shape of the scene: a holistic representation of the spatial envelope. IJCV, 42, 2001.

[10] International Journal of Multimedia and Ubiquitous Engineering Vol. 8, No. 4, July, 2013 385 A Review on Image Feature Extraction and Representation Techniques Dong ping Tian.

[11] Veremeyenko K. K. and others. Modern information technologies in the UAV navigation and targeting tasks./ Edited by M.N. Krasilschikov, H.H. Serebryakov – Moscow, Physmathlit, 2009.- 556p.

[12] Gruzman I.S., Kirichuk V.S., Kosyh V.P., Peretyagin G.I., Spector A.A. Digital images processing in information systems. Manual.- Novosibirsk: Printing house of NSTU, 2002.- 352 p.

[13] Subbotin S.V., Bolshakov D.Yu. Application of Bayes classificator for recognition of targets classes. // "Journal of radionics", 2006, № 4 (availableonline).

[14] P.-J. Nordlund. Sequential Monte Carlo Filters and Integrated Navigation. Licenciate thesis, LinkÄopings University, 2002.

[15] Li X. R., Jilkov V. P. Survey of maneuvering target tracking. Part I. Dynamic models //Aerospace and Electronic Systems, IEEE Transactions on. – 2003. – Т. 39. – №. 4. – С. 1333-1364.

[16] Bay H. SURF: Speeded Up Robust Features / Bay H., Tuytelaars T., L. Van Gool // European Conference on Computer Vision. Graz ( Austria). – 2006. – Vol. 1. – p. 404-417.



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