UDC 519.6

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Development and research of the algorithm search of the singular points position in the aircraft vision systems

The paper deals with the feature detection problem in aircraft machine vision systems. We developed a fast detection algorithm. We determined feature locations in an image sequence depicting fast-moving objects as registered by aircraft machine vision systems. We analysed existing feature detection algorithms. The input image frame sequence undergoes a geometric transformation, that is, rotation. We simulated how our algorithm processed a sequence of frames depicting the target. We compared efficiency and speed of feature detection in the well-known SIFT algorithm with that of our algorithm. We demonstrate that the algorithm developed ensures faster feature detection that is more resistant to geometric transformations of the target image as compared to the SIFT algorithm.

Keywords: features, machine vision system, descriptor, fast-moving objects, geometric transformation.

Introduction

Machine vision systems (MVS) are designed for acquiring visual environmental data by means of technical equipment in different spectral ranges. Another function is image processing and analysis for further object classification. Visual data processing is intended to get an idea of the scene, acquire its imagery, and describe the object under observation for further classification. This task perfectly correlates with functions of modern airborne MVSs. On the one hand, the description shall contain all essential information about the object under observation, on the other hand – ensure high-quality image processing with minimum time expenditures. When an object image is described by means of MVS, some required information is extracted with certain data loss in total. The most important task of MVS is to balance these two processes [1].

Let us discuss the key features that define the specifics of development of particular MVSs for advanced aircraft.

First of all, development of MVS information support subsystems requires a solution not to the general problem related to automatic recognition of random imagery, but to a more specific and focused task related to the problem-oriented interpretation of an object image. Often this task comes down to detection and identification of a certain set of keypoints (KP) in an object image, the presence of which may affect the problem-solving process.

Secondly, image processing algorithms implemented into MVS shall meet special requirements regarding the purpose and characteristics of an existing system or a system being developed. The aircraft attitude dynamically changes, depending on time. Therefore, an image analysis subsystem shall meet the following requirements based on the problem specifics: robustness, localization and real-time computational feasibility within the selected hardware architecture. Generally, MVS functioning is a real-time process that requires a solution to the typical discrepancy between requirements for quick response of a system and requirements for memory volume to be reduced [2].

One of important problems related to the process of object image extraction by means of MVS is comparison of an image extracted from a photo or video frame with its reference samples stored in a database. The basic method for solving the problem is to match a subset of image KPs (point features) and relevant subsets of object reference sample KPs. Applicable image recognition tools are based on various methods of matching recognizable objects and their patterns stored in the database.

KP is a keypoint in the aircraft image, which has clearly defined positions in adjacent frames and can be identified accurately for further classification of the object under observation. KP has some features that make it different from a set of adjacent points of the current image object. KP may represent typical elements in object images, for example, angles, apex points, small circumferences and circles, plane edges, abrupt colour transitions, jumps in brightness or in contrast. Actually, a keypoint may be an isolated local maximum or local minimum point of the intensity line or may be represented as the most primitive element of the discrete representation of the object description function.

Despite the fact that an aircraft image represented as a set of keypoints is a simple structure – a matrix of two-dimensional numbers, which comprises a great amount of information on the scene being observed, it is a challenging task to extract structured information from the scene. If we talk about a sequence of images showing highly dynamic objects, we have to face a more complex problem, because spatio-temporal relations appear between frames. We need to validate an algorithm, which will enable fast detection and identification of the KP portion in a sequence of object images in real time.

This paper is intended to develop an algorithm for fast detection and identification of keypoint positions in a sequence of images of highly dynamic objects to be implemented into aircraft machine vision systems.

Comparative analysis of algorithms for description and correlation of KP descriptors

In order to recognize a certain KP in the image frame, we shall find it using a detector and select a descriptor vector for every point found. Such a vector describes the structure of the point neighbourhood making it different from a set of other points found.

A set of KP descriptors can identify an object model in the image. This model is used for further matching with its reference images stored in the database. Based on an analysis of the set of initial object descriptors arranged in pairs and object’s reference images, the system can make a decision whether the matched images are similar to each other.

Descriptors are matched as follows. A set of pairs of the nearest descriptors is selected within the classification. The extent of proximity is calculated as the length of the descriptor vector in the image area. Then, based on selected pairs of the nearest descriptors, the system makes a decision whether the initial image matches its reference sample by comparing distances with regard to a certain threshold.

So far, a lot of KP detection algorithms have been developed, including various detectors and description of the neighbourhood of the detected point. Below is the list of widely known algorithms.

1. *SIFT* (*Scale Invariant Feature Transform*) algorithm. Point neighbourhood descriptors are invariant to image scaling and rotation and are tolerant to illumination variations, noise, and observer’s line of sight. *SIFT* is one of the most popular algorithms describing KP descriptors.

2. *SURF* (*Speeded Up Robust Features*) algorithm. Point neighbourhood descriptors are invariant to image scaling and rotation as well, because the neighbourhood of the detected point is described by means of the Hesse matrix. The maximum brightness variation gradient in a given area along with the scaling coefficient is calculated for each KP using the Hesse matrix.

3. *RIFF* (*Rotation Invariant Fast Features*) algorithm. Similarly to the above-mentioned algorithms, this descriptor is invariant to image scaling, rotation, and illumination variation. It is based on radial and tangential expansion of gradient histograms and further processing by radial bins.

The algorithms listed above have their advantages and disadvantages. The main disadvantage of the *SIFT* and *SURF* algorithms is unstable extraction of KPs at a low signal-to-noise ratio, as well as low percentage of correct recognition of object image elements without an explicit texture. Instability of the *RIFF* algorithm is caused by image blurring due to the presence of interframe mismatch [3].

Theoretical studies

Real-time processing of a video frame sequence is the essential requirement for MVS, that is why needless computational complexity of *SIFT*, *SURF*, and *RIFF* algorithms is their unwanted feature. To address the problem, we have proposed an algorithm for fast detection and identification of KP position in a sequence of aircraft images due to a substantial decrease in the amount of input data. The proposed algorithm is based on an analysis of statistical distribution of points in a binary aircraft image.

Once a sequence of images is obtained, they are subject to pre-processing in order to prepare a sequence of aircraft image frames for further processing and analysis. The image pre-processing algorithm includes image filtering to enhance image sharpness, plus binarization and data analysis to be followed by morphological processing (Fig. 1).

Generally, images generated by various information systems are distorted if exposed to interference. This hampers visual image analysis performed by a human operator or through computer-aided automatic processing. Some image components may interfere with the problem-solving process regarding image processing. For instance, an analysis of satellite images of the Earth surface may require the identification of boundaries between individual surface areas (boundaries between a forest and a field, between water and land, etc.). In accordance with the stated problem, individual image details inside areas to be separated are considered to be interference.

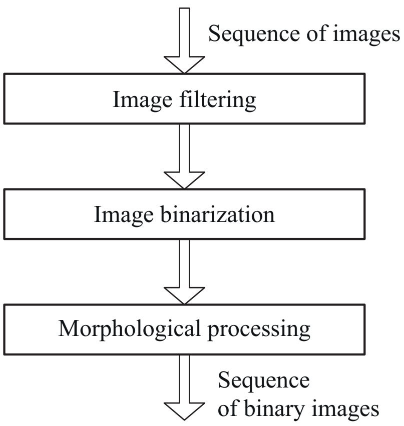


Fig. 1. Block diagram of image pre-processing algorithm

Linear spatial filleting can help diminish the impact of high-frequency and impulse interference. With active filtering, the brightness (signal) of each point in the initial image distorted by interference is changed to the other brightness value, which is assumed to be distorted by interference least of all.

Image binarization is the key aspect determining the quality of KP detection algorithm execution. The use of this operation allows to divide an image into components of its conceptual domains. The binarization result is generally represented as an image with the amount of elements equal to that of the reference image. Thus, a video sequence is generally regarded as input data for binarization.

There is a lot of methods to solve the binarization problem. Such methods have their own advantages and disadvantages [4]. Most of them are based on the analysis of image point features. Point features are scalar or vector values computed with the help of the image brightness field. Selection of features has a decisive effect on correct binarization.

It is known that in order to achieve satisfactory results in solving the binarization problem, it is necessary to select a proper system of features for object description [4]. The existing binarization algorithms [4] are divided into binarization with low threshold value, high threshold value, double threshold, etc.

The proposed algorithm for fast KP detection uses a bitmap image brightness distribution histogram as input data. The histogram is plotted based on the following values

$$p_i = n_i / N,$$

where n_i – amount of pixels with brightness level i;

N – total amount of image pixels.

The brightness range is divided into two classes using brightness level threshold k, which has the integer value in the range of 0...L. Each class corresponds to relative frequencies ω_0, ω_1:

$$\omega_0(k) = \sum_{i=1}^{k} p_i; \quad (1)$$

$$\omega_1(k) = \sum_{i=k+1}^{L} p_i = 1 - \omega_0(k); \quad (2)$$

$$\mu_0(k) = \sum_{i=1}^{k} \frac{i \times p_i}{\omega_0}; \quad (3)$$

$$\mu_1(k) = \sum_{i=k+1}^{L} \frac{i \times p_i}{\omega_1}, \quad (4)$$

where μ_0, μ_1 – average brightness of the whole image.

Below we will calculate the maximum value of quality assessment regarding an image divided into two parts:

$$\eta(k) = \max_{k=1}^{L-1}\left(\frac{\sigma^2_{\text{кл}}(k)}{\sigma^2_{\text{общ}}}\right), \quad (5)$$

where $\sigma^2_{\text{кл}}$ – interclass dispersion;

$\sigma^2_{\text{кл}} = \omega_0\omega_1(\mu_1 - \mu_0)^2$;

$\sigma^2_{\text{общ}}$ – total dispersion of the whole image.

After image binarizarion within the domain is completed, images are subject to morphological processing. First of all, mathematical morphology is employed for extracting certain properties of the image needed for its representation and description, for example, contours, skeletons or convex hulls. The basic operations of mathematical morphology are dilation, erosion, closing, and opening. Obtained collections of pixels shall be described and represented in the form fit for further computer-aided processing. The domain is represented by means of internal characteristics (i.e. a collection of image elements representing the domain). Generally, internal representation is selected when the interest is in the properties of the domain, for example, its colour and texture. In this case, they form its weight. The object weight is viewed as a sum of points a given object consists of.

Keypoints are analysed and detected in binary images where all the binary objects shall be identified. Then lists of binary objects and features of each object are compiled.

Let us assume that current image $M(x, y)$ has a certain amount of binary objects (N). A three-dimensional vector is created for each object.

$$\mathbf{A}_N(x, y, z),$$

where x, y – coordinates of the object’s centre of mass;

z – object weight (one of the features).

Further, based on an array of vectors, we shall determine distance matrix $\|r_{ij}\|$ as follows:

	A_1	A_2	...	A_i	...	A_N
A_1	0	r_{12}	...	r_{1i}	...	r_{1N}
A_2		0	...	r_{2i}	...	r_{2N}
...			...	...	...	...
A_k				0	...	r_{iN}
...					...	
A_N						0

Here, the Euclidean distance between A_i and A_k is calculated as follows

$$r_{ij} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2}, \quad (6)$$

where x_i, y_i, x_k, y_k – image KP coordinates.

Then lets us transform the matrix into a row vector, the elements of which are the expected values of the column vector of distance matrix $\|r_{ij}\|$:

$$\mathbf{M}(X) = \sum_{i=1}^{n} x_i \times p_i. \quad (7)$$

Based on the resulted expected values, we will detect three checkpoints with maximum expected values. The KP with the maximum expected value will become the central point to be used as the origin for further transformations.

The KP positioning accuracy is the most significant criterion for algorithms of evaluation and compensation of geometric transformations of images to be processed. Assurance of high accuracy is one of the key issues related to image recognition and matching using MVS.

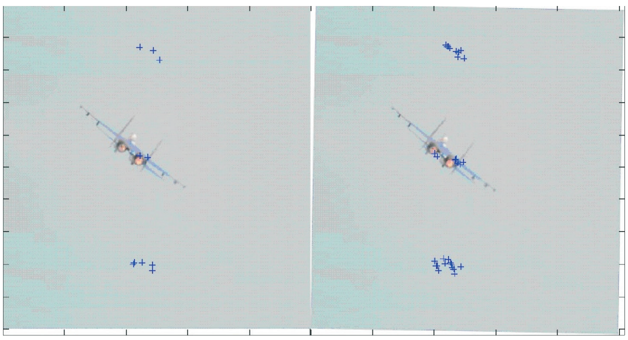
Experimental studies

We have compared the proposed algorithms intended for KP fast detection and position identification with *SIFT,* the most frequently used algorithm for describing keypoint descriptors in the *MATLAB* environment.

We have used low-contrast images of various aircraft as input data. Moreover, one image has been subject to geometric transformation (rotation) relative to another. The amount of detected KPs has been viewed as the performance criterion.

Let us assume that the mismatch between two aircraft images relative to the centre is 1°. Using the *SIFT* algorithm, we have detected 118 points in the first image and 158 points in the second one (Fig. 2). Amongst the detected KPs, only 43 points are junction points (i.e. points with the same descriptors in two different images).

Based on experiment results, we may conclude that even rotation of the aircraft image through a small angle gives a great amount of false positive results when detecting keypoints using the *SIFT* algorithm. Fig. 2 clearly shows the presence of junction points beyond the object under observation (aircraft).

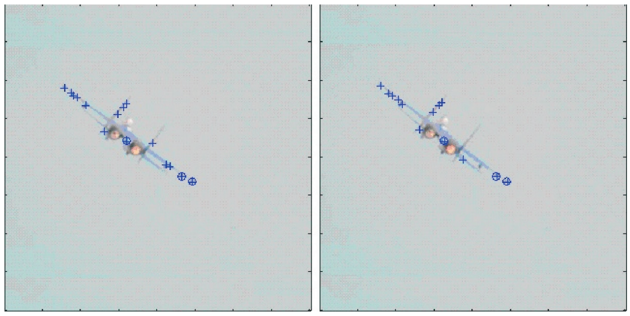


a b

Fig. 2. Result of keypoint application using the *SIFT* method for KP detection:
a – initial image; b – image with angle mismatch of 1°

Fig. 3 shows the results of initial image analysis and processing using the proposed algorithm. The proposed algorithm allows to identify 15 points in the first image (Fig. 3, a) and 13 points in the second one (Fig. 3, b), with 3 junction keypoints only.

As for the second experiment, the mismatch between two images relative to the centre has reached 10°. Using the *SIFT* algorithm, we have detected 118 KPs (Fig. 4, a) in the first image and 248 KPs in the second one, including 16 junction points only.



a b

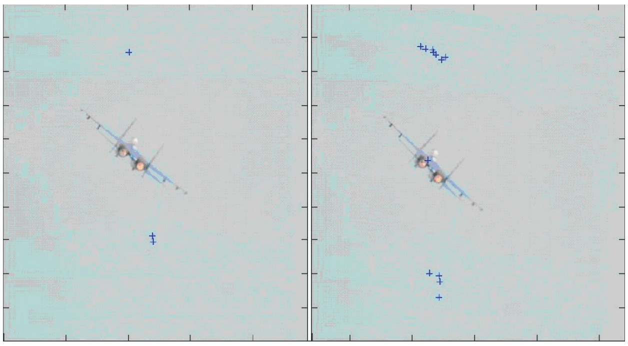
Fig. 3. Result of KP detection using the developed algorithm:
a – initial image; b – image with angle mismatch of 1°

Based on the second experiment results, we have found out that the invariant property of the *SIFT* algorithm is definitely reduced when an image is rotated through an angle of no more than 10°. Therefore, the limiting properties of the *SIFT* algorithm have been confirmed when an image is rotated through 10°.

We have applied the same technique for testing the proposed algorithm for fast detection of KPs in two images. The mismatch has totalled 10° relative to the centre.

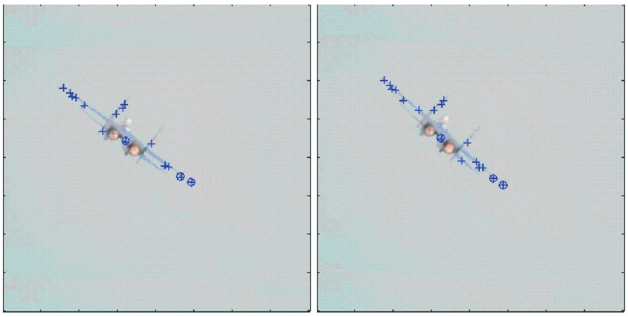
Fig. 5 shows 15 points detected by means of the proposed algorithm for fast detection of KPs. Fig. 5, b shows 13 points, including 3 junction points detected.

As for the third experiment, the mismatch between two images relative to the centre has totalled 90°. Using the *SIFT* algorithm, we have detected 118 points in the first image and 88 points



a b

Fig. 4. Result of keypoint detection using the *SIFT* method for KP detection: a – initial image; b – image with angle mismatch of 10°



a b

Fig. 5. Result of keypoint detection using the proposed algorithm: a – initial image; b – image with angle mismatch of 10°

in the second one. No junction points have been found.

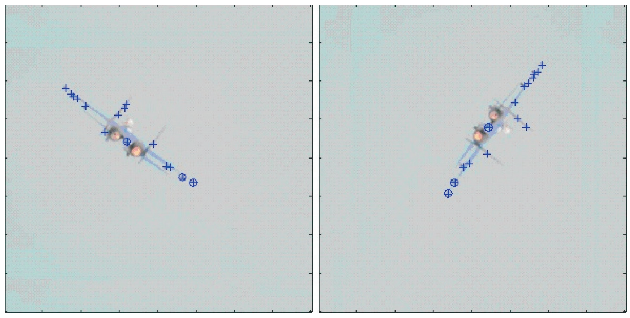
Using the proposed algorithm for fast detection of KPs, we have detected 15 points in the first image (Fig. 6, a) and 15 points, including only 3 junction points in the second one (Fig. 6, b).

Results of comparison of time periods spent for computations at different angle mismatch are given in the table.

The table data proves that the developed algorithm has an advantage in computing speed in comparison to the *SIFT* algorithm.

Conclusion

We have analysed the existing KP detection algorithms implemented into MVS and revealed their main advantages and disadvantages. We have developed an algorithm for fast detection



a b

Fig. 6. Result of keypoint detection using the proposed algorithm: a – initial image; b – image with angle mismatch of 90°

Computation time at different angle mismatch

Rotation angle	Algorithm	Time, s
1°	*SIFT*	3.46
	Proposed	0.63
10°	*SIFT*	3.88
	Proposed	0.61
90°	*SIFT*	3.55
	Proposed	0.64

of keypoints based on the analysis of statistical distribution of a binary image.

We have analysed the performance of the well-known *SIFT* algorithm for keypoint detection in comparison to the proposed fast detection algorithm using a sequence of two frames of a low-contrast image with different angle mismatch.

As a result, the main disadvantages of the *SIFT* algorithm have been proven [5, 6], such as inaccurate extraction of aircraft image keypoints relative to the background; low percentage of correct recognition of object image elements without explicit texture; invariance to angle mismatch of no more than 10°. The obtained results prove that the proposed KP detection algorithm is tolerant to image rotation. Based on experimental studies, we may conclude that the proposed algorithm is invariant to aircraft angle mismatch.

We have proven that the amount of input data can by reduced to a great extent. This allows to ease the computational complexity of the algorithm and to lower the requirement for hardware processing speed. In its turn, this requirement is the basic criterion for selecting real-time data processing algorithms to be implemented by aircraft MVS.

The obtained results can be used for smart optical data processing, image recognition and decision-making systems for applications related to weapon classes such as Man-Portable Surface-to-Air Missile Complex (MANSAMC) and Anti-Tank Guided Missile (ATGM).

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Submitted on 06.03.2018

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Разработка и исследование алгоритма поиска положения особых точек в системах технического зрения летательных аппаратов

Рассмотрена задача поиска положения особых точек в системах технического зрения летательных аппаратов. Разработан алгоритм быстрого поиска. Определены положения особых точек в последовательности изображений высокодинамичных объектов в системах технического зрения летательных аппаратов. Проведен анализ существующих алгоритмов поиска особых точек. Входная последовательность кадров изображений подвержена геометрическому преобразованию – повороту. Осуществлено моделирование разработанного алгоритма на последовательности кадров наблюдаемого объекта. Проведено сравнение эффективности и быстродействия поиска особых точек известного алгоритма *SIFT* с предложенным алгоритмом. Показано, что разработанный алгоритм обеспечивает более быстрый и устойчивый к геометрическому преобразованию изображения наблюдаемого объекта поиск особых точек по сравнению с алгоритмом *SIFT*.

Ключевые слова: особые точки, система технического зрения, дескриптор, высокодинамичные объекты, геометрическое преобразование.

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