

AUTOMATIC TARGET RECOGNITION OF COMPLEX INTERNAL STRUCTURE

Tadeusz Niedziela

Warsaw University of Technology, Faculty of Transport, Warsaw, Poland
e-mail: tniedz@wt.pw.edu.pl

Abstract: *The paper presents methods of automatic target recognition from images with complex internal structure. Recognition methods proposed are based on the Fourier transform properties. These methods make it possible to bring the problem to Fourier transform, feature extraction and input image classification. Image data synthesis within diffraction plane significantly increases the probability of target detection.*

Key words: *Automatic Target Recognition, ATR, target detection, Fourier transform*

1. Introduction

Automatic Target Recognition (ATR) from images within diffraction plane is a current and important research problem aiming at designing simple and efficient systems having measurable practical advantages [1-9]. Classic algorithms of automatic recognition are composed of two stages: feature extraction of objects from real environment in which there can be a high level of noise; and classification or identification. A crucial role among such systems is played by opto-electronic systems.

In general, the contemporary methods of pattern recognition can be divided into electronic, optical and opto-electronic (hybrid) [3].

Characteristic features of an object can be extracted directly from an image or from its transform. Whether the features are detected from the image or from its transform depends on the type of image. Images of complicated internal structure (texture) are easier to be recognized within the space of their transforms, whereas images of poor structure are easier to be recognized through features indicated directly from the image. Construction of the feature vector allows for significant reduction of the amount of information to be further processed and accelerates recognition process.

Identity or similarity of recognized objects can be concluded on the basis of the difference of feature vectors, both within the space of the image as well as the transform.

Numerous researchers and firms undertake construction of fast, reliable and easily adaptable automatic systems of diffraction pattern recognition. Research work is focused on completely optical systems, limited mainly by the technology of optical neural networks. Indirect

solutions are opto-electronic (hybrid) methods. Development of diffraction pattern recognition techniques allows for designing more efficient systems of target recognition characterized by complex internal structure.

Feature extractor and classifier are basic modules which determine the quality of recognition systems. For many years, the feature extractor in the form of a photodiode matrix in the shape of wedges and half-rings (ring-wedge detector) ensured sufficient diffraction pattern recognition. However, its main limitation is a high cost and low adaptability because of the same measurements of sampling elements.

Successful command of feature extractor technology in the form of diffraction gratings of variable refractive index (computer-generated holograms) and photodiode matrices of high density package caused significant progress in the construction of automatic systems of diffraction pattern recognition. Therefore, the necessity arose for designing methods of extractor optimization (in view of the number of areas and size of sampling elements). These types of activity resulted in obtaining very low normalized decision errors of recognition systems.

2. Opto-electronic system of pattern recognition within diffraction plane

An image transformed by Fourier transform is equivalent to the original image. Information included both in the former and in the latter version of the image is identical, however presented in various forms. When speaking about a real image, we deal with such notions as picture element (pixel), its coordinates (x, y) and intensity $g(x, y)$.

Whereas, Fourier image $G(f_x, f_y)$ is described by such notions as image patterns, their spatial frequencies (f_x, f_y expressed in lines /mm) and directions of these structures. Information included in Fourier image is synthetic because it describes not a single picture element but their sets called patterns. Fourier transform is invariant due to translations but depends on the change of scale and rotation.

Fourier transform can be realized in an optical, digital or electronic way. Optical methods of Fourier transform realization are simple and at present they find various applications. The concept of opto-electronic pattern recognition within diffraction plane has been illustrated in fig.1.

2.1. Feature extractor in the form of a ring-wedge detector (RWD)

If the feature extractor (ring-wedge photodiode matrix RWD) is placed in the rear focal plane of a lens (referred to as Fourier plane), possibility arises of sampling Fraunhofer diffraction patterns – sampling of spectral power which is focused on half-rings and wedges. Thus, each area of the extractor generates exactly one characteristic feature (fig.2), calculated as an integral of power spectrum focused on the sampling element.

The known Fraunhofer approximation of Fresnel-Kirchhoff integral realized by a lens can be expressed as [8]:

$$F(\xi, \eta, z) = \frac{iE_0}{\lambda z} e^{-i\frac{\pi}{\lambda z}(\xi^2 + \eta^2)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{i\frac{2\pi}{\lambda z}(x\xi + y\eta)} dx dy \quad (1)$$

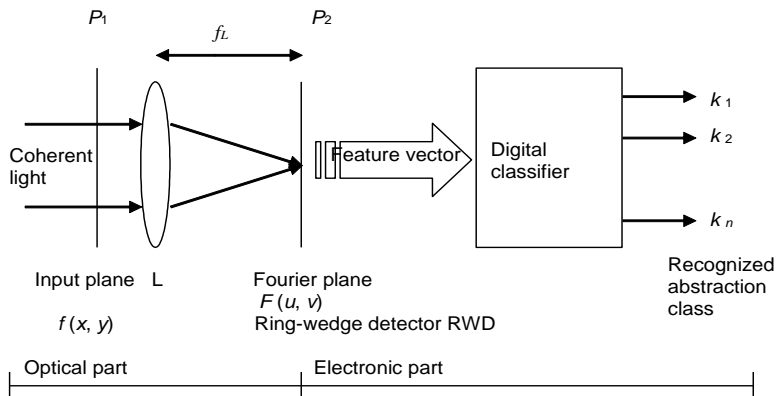


Fig. 1. Schematic diagram of opto-electronic recognition of images with complex internal structure

which in consequence gives Fourier transform of the input function $f(x, y)$ together with multiplication of the result by spherical phase parameter. As it is only intensity that can be directly observed and registered in practical applications, the parameter of spherical phase can be omitted. Intensity is therefore Fourier spectral power $F^2(u, v)$ of the input function transmittance $f(x, y)$, which is called Fraunhofer diffraction pattern and is observed from infinity to the rear focal plane of a spherical lens.

If Fraunhofer diffraction pattern (F) is expressed in polar coordinates (ω, ϕ), then characteristic features corresponding with rings R_i and features corresponding with wedges W_i are defined by the expression:

$$W_i = \int_0^R \left(\int_{\phi_i}^{\phi_{i+1}} F^2(\omega, \phi) d\phi \right) d\omega \quad (2)$$

$$R_i = \int_0^\pi \left(\int_{r_i}^{r_{i+1}} F^2(\omega, \phi) d\omega \right) d\phi$$

where: r_i and r_{i+1} indicate the internal and external radius of the ring *RING* (i) respectively, ϕ_i and ϕ_{i+1} indicate the initial and final angle of the wedge *WEDGE* (i) respectively, ϕ_j ($j = 1, \dots, N_w$), R is the radius of the ring-wedge detector (RWD), N_R and N_w are the integers of rings and wedges respectively.

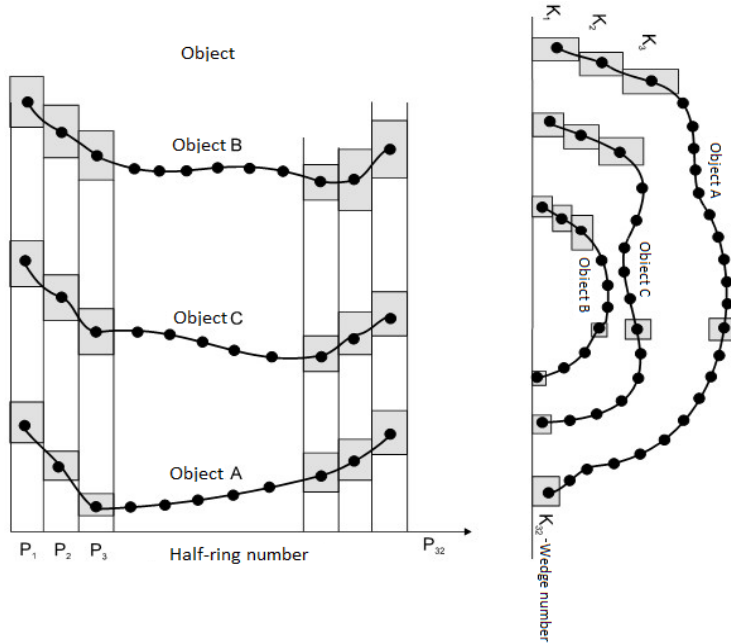


Fig. 2 Schematic diagram of feature vector generation for three different objects (A, B, C) obtained from the ring-wedge detector

The values of features R_i are invariant with reference to the shift and rotation of the input image, but dependent on the change of scale (enlargement of the input image a times causes times reduction of the spectral image).

The values of features W_i are invariant with reference to the shift and the change of scale of the input image, but dependent on rotation.

Which invariances and which dependencies in a feature vector are important in practice is a problem within itself.

2.2. Feature classifier in the form of an artificial neural network ANN

Noise in images is most often the sum of elementary noises caused by various independent phenomena and characterizes of Gaussian distribution, hence classification should be realized on the basis of statistical model of uncertainty. In this model the expected conditional probability $P(C/x)$ (*a posteriori*) is used as a decision criterion of minimizing average losses caused by wrong classification. If δ indicates classification

operations, then classification criterion is the following:

$$\delta(\mathbf{x}) = C_k \Leftrightarrow \forall_{j \neq k} P(C_k | \mathbf{x}) > P(C_j | \mathbf{x}) \tag{3}$$

where: \mathbf{x} is a feature vector, and C_k and C_j are recognized classes k and j respectively.

Multilayer perceptrons are very often used as classifiers because after adequate training they realize at the output y_k approximation of conditional probability (*a posteriori*) $P(C_k | x)$ of appearance of a given class C_k if at their input a feature vector \mathbf{x} is given. This is the most desired feature in recognition by means of random uncertainty model because these probabilities are used in the decision rule (3). Thus, it can be easily noticed that from a statistical classifier a binary classifier can be obtained.

The present paper proposes statistical classifier as probabilistic neural network (PNN). Such networks constituting kernel estimators of probability density function are built as a special kind of radial neural

networks dedicated to estimation of probability density function.

From the point of view of network architecture, probabilistic neural networks is a three-layer network (fig. 3) without feedback. It consists of input layer, pattern layer and summation layer.

The input layer consists of N elements in order to process N -dimensional feature vectors generated by the feature extractor (RWD - ($N = N_R + N_W$)).

The pattern layer consists of M groups of pattern neurons associated with M classes. In this layer, radial neurons are proposed with Gaussian transfer function. Each neuron of the pattern layer is connected with each neuron of the input layer, and weight vectors of the pattern layer are equal to characteristic features from the teaching set. Contrary to the pattern layer, the summation layer consisting of M neurons is organized in such a way that only one output neuron is connected with neurons from any pattern group.

2.3. Difference algorithm of ring order of diffraction patterns within Fourier plane

The present chapter proposes a simple difference algorithm of ring order for diffraction pattern recognition. This algorithm compares values of feature vectors of real images obtained from wedges, with the feature vector of the pattern image. The pattern object characterizes a unique value and proper proportions of data in the feature vector coming from wedges.

A real object belonging to the same class as the pattern object has a similar value of the feature

vector, however, with a different placement, the level of particular components and disruptions connected with image acquisition.

Let us define the feature vector of the pattern image as:

$$r^1 = (r_1^1, r_2^1, \dots, r_n^1) \quad (4)$$

and the feature vector of the real image (amplitudes of signals for the recognized diffraction pattern):

$$r^2 = (r_1^2, r_2^2, \dots, r_n^2) \quad (5)$$

Then, let us make a change in amplitude ordering. Let us assume amplitude ordering (from the highest to the lowest amplitude) for diffraction pattern of the pattern image

$$s^1 = (r_1^1, r_2^1, \dots, r_n^1) \quad (6)$$

Analogically, the sequence of amplitude ordering (from the highest to the lowest amplitude) for diffraction pattern of the recognized image

$$s^2 = (r_1^2, r_2^2, \dots, r_n^2) \quad (7)$$

Let us define the measure of similarity of the two diffraction patterns as:

$$S(s^1, s^2) = \sum_{w=1}^n |r_w^1 - r_w^2| \quad (8)$$

where: w – wedge index.

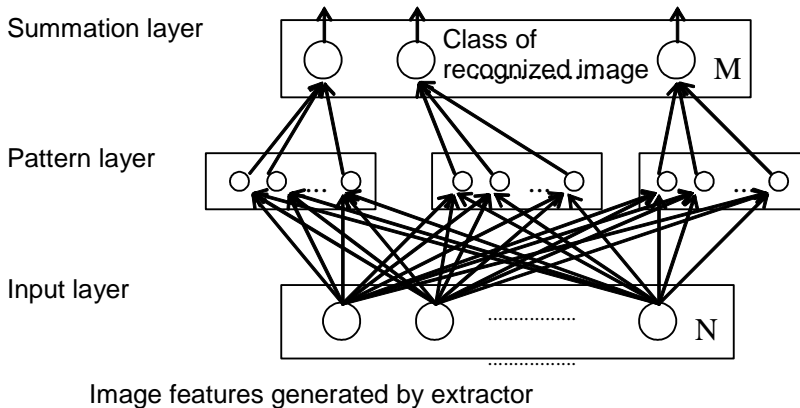


Fig. 3. Probabilistic neural network as a classifier of characteristic features generated by a feature extractor

The minimum distance between the pattern and the tested vector is:

$$\hat{S}(s^1, s^2) = \min S(s^1 @ s^2) \tag{9}$$

In order to find the minimum distance between the vectors, we should turn one of the vectors by one wedge per measurement. This could be done by changing indices of feature vectors of the real image. Each index indicating subsequent position of the vector should be decreased by one:

$$x_1 = (m_1^1, m_2^1, \dots, m_n^1) \tag{10}$$

$$m_k^1 = \begin{cases} k = n \text{ then } & k = k - n + 1 \\ \text{otherwise} & k = k - 1 \end{cases} \tag{11}$$

where: k – value of index describing the element number in the feature vector.

Fig. 4 and fig. 5 illustrate difference algorithm of ring ordering for diffraction patterns within Fourier plane.

Algorithm of the wedge-difference sum experimentally proved its quality in practice and can be successfully applied for images of complex internal structure (e.g. in criminology in recognition of fingerprints, handwriting or faces). The algorithm is convenient and efficient because in a simple way it compares feature vectors. These vectors include much less data than diffraction patterns, therefore, this method is quite fast from the point of view of calculation.

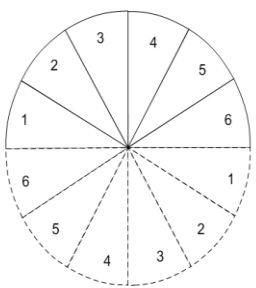
Sample wedge detector	Pattern (I)		Real image (II)		
	Wedge	Amplitude	Order according to value	Amplitude	Order according to value
	1	400	3	2000	1
	2	50	6	150	5
	3	1000	1	400	4
	4	75	5	1000	2
	5	200	4	800	3
	6	500	2	100	6

Fig. 4. Sample values of the pattern and real feature vector obtained from the wedge detector

ALGORITHM	I	II	Δ	Rotation of a feature vector of a real images by two wedges	I	II	Δ	High similarity
	3	1	2		3	3	0	
	6	5	1		6	6	0	
	1	4	3		1	1	0	
	5	2	3		5	5	0	
	4	3	1		4	4	0	
	2	6	4		2	2	0	
	Σ	Σ	14		Σ	Σ	0	

Fig. 5. Algorithm of automatic target recognition with the use of the wedge detector

3. Digital system of pattern recognition

Despite undeniable positive features of opto-electronic detection systems based on feature extractors in the form of a ring-wedge detector matrix, systems of this type have significantly limited applications due to the high cost and their low level of flexibility. At present, intense research work is being conducted over substituting feature extractors based on RWD technology with neural extractors which are focused on miniaturization and cost reduction [10, 11]. The proposed digital system constitutes an alternative for opto-electronic methods, theoretically ensuring operation within the time approximate to real time.

The basis of the proposed method is proper sampling of the diffraction pattern by the feature extractor in the form of a neural rectangular detector (RD), thanks to which information included in the feature vector extracted by neural network is invariant because of rotation, change of scale and shift.

The proposed digital system of automatic recognition (fig. 6) consists of: neural block of Fourier transform (ANNF), neural feature extractor (ANNRD) in the form of rectangular detector (RD) and neural classifier (ANNBP) taught by means of the method of backward propagation of error. Thanks to such construction, the whole system has the form of a hierarchical neural network.

Since the sampling of images in the form of discrete matrices is conducted by means of input data, it is best to realize the stage of Fourier transforms with the use of discrete methods. Fourier transform in view of the character of input data is realized by one-layer specialized neural network (ANNF).

Detection of the feature vector is realized by rectangular neural detector (RD) placed in the ANNRD block.

Such organization of calculations makes it possible to build a system operating in the time approximate to real time. Recognition speed is significant for applications where recognition quality and response time of the system are key criteria.

3.1 Neural network realizing Fourier transform (ANNF)

Instead of optical Fourier transform, we can propose the slow discrete Fourier transform (DFT) or its faster version – fast Fourier transform (FFT). The latter because of its efficiency is readily applied for testing solutions. Yet another solution is application of neural network. The original proposal presents paper [12], in which the author proposed the structure of neural network calculating Fourier transform with neurons based on biological neurons of type $\Sigma\Pi$.

The author of the present paper proposes a similar solution resulting directly from the equation describing DFT

$$F(u, v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)},$$

for the two-dimensional discrete input image this equation takes the form of

$$y^{(u,v)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(m, n) w_{(m,n)}^{(u,v)}$$

$$y^{(u,v)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(m,n) W_{(m,n)}^{(u,v)} \text{ where: } m, nm, n - \text{ numbers}$$

of neuron input for the two-dimensional image, u, v – number assigning the neuron to the two-dimensional Fourier transform, M, NM, N – input image size) and the equation $(y^{(m)} = \sum_{i=1}^n w_{(i)}^{(m)} x_i$

where: m – number of output neuron, i – number of neuron input) describing operation of one-layer neural network. The proposed network does not have the teaching capability. The weights of connections are established at the stage of network design. Their values are determined by the size of the input and output image.

Comparing the equation describing operations of two-dimensional discrete Fourier transform and a simpler one-layer neural network, it is easy to notice certain similarities that each Fourier picture element is a sum of all picture elements of the input image burdened by a certain coefficient connected

with the kernel of Fourier transform $(e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)})$. In both cases (for DFT and ANN), the input and output image can differ in size, whereas the relation between the input and output matrix is similarly described (the kernel of Fourier transform or weight matrix for ANN).

Fourier transform integrates the values of all pixels of the input image with a certain coefficient $1/MN$, similarly to the neuron in a simple one-layer perceptron. In both cases the component of a single pixel of the output image is the sum of all pixels of

the input image $(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n)$ – the integral

component of Fourier transform) burdened by a certain weight. The equivalent of weighing matrix \bar{w} , of the neuron is the matrix created by the

kernel of Fourier transform (kernel = $e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)}$). Similarly to the weighing matrix \bar{w} , the kernel of Fourier transform constitutes a relation between the input and output image. This matrix for ANNF is created at the design stage and does not change. The values of weighing matrix for the neuron are created by calculating the kernel of Fourier transform for each connection.

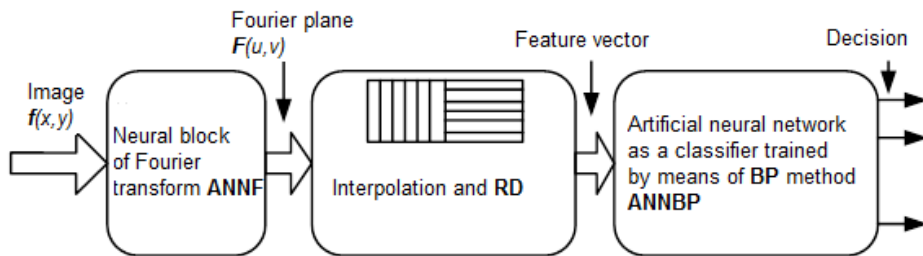


Fig. 6. ARO System in the form of a hierarchical neural network consisting of threespecialized ANN subsequently realizing: Fourier transform, characteristic feature detection and classification

The two-dimensional Fourier transform for real images has complex values, therefore, each picture element of Fourier image calculated by the proposed network has two components: real and complex, thus, it will be a matrix of complex values.

$$Kernel = re(kernel) + im(kernel) \quad Kernel = re(kernel) + im(kernel)$$

The implication of this property is twice bigger number of neurons (fig. 7) and simultaneously twice bigger number of neurons than picture elements of output image. Pairs of neurons *re* and *im* have been named Fourier neurons.

For the two-dimensional case:

$$kernel = e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)} \quad (12)$$

that is

$$kernel = re\left(e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)}\right) + im\left(e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)}\right) \quad (13)$$

For the concrete connection between the picture point of the input image $f(m,n)$ and the picture point of the output image $F(u,v)$ we obtain:

$$kernel = re(kernel(m,n,u,v)) + im(kernel(m,n,u,v)) \quad (14)$$

where:

m,n – number of neuron input for the two-dimensional image;

u,v – number of neuron output for the two-dimensional Fourier transform.

For the one-dimensional Fourier transform:

$$F(u) = \frac{1}{M} \sum_{m=0}^{M-1} f(m) e^{-i2\pi\left(\frac{mu}{M}\right)} \quad (15)$$

the kernel of the transform constitutes:

$$kernel = e^{-i2\pi\left(\frac{mu}{M}\right)} \quad (16)$$

that is

$$kernel = re\left(e^{-i2\pi\left(\frac{mu}{M}\right)}\right) + im\left(e^{-i2\pi\left(\frac{mu}{M}\right)}\right) \quad (17)$$

therefore we obtain:

$$kernel = re(kernel) + im(kernel) \quad (18)$$

For the connection between the picture element of the input image $f(m)$ and the picture element of the output image $F(u)$ we obtain:

$$kernel(m,u) = re(kernel(m,u)) + im(kernel(m,u))$$

where:

m – number of neuron input;

u – number of neuron.

Therefore, the weight m – of this double neuron input:

$$w_m^{re} = re\left(e^{-i2\pi\left(\frac{mu}{M}\right)}\right) \quad (19)$$

$$w_m^{im} = im\left(e^{-i2\pi\left(\frac{mu}{M}\right)}\right) \quad (20)$$

Hence, for the two-dimensional case:

$$w_{(m,n)}^{(u,v)re} = re\left(e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)}\right) \quad (21)$$

$$w_{(m,n)}^{(u,v)im} = im\left(e^{-i2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)}\right) \quad (22)$$

The network response for the two-dimensional case is described by the equation:

$$y^{(u,v)} = \frac{1}{MN} \left(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{(m,n)} w_{(m,n)}^{(u,v)re} + \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{(m,n)} w_{(m,n)}^{(u,v)im} \right) \quad (23)$$

The result of calculations of Fourier transform is a matrix of complex elements. For obtaining information about the amplitude within spatial frequency function (u,v) , power spectrum distribution should be calculated $|F(u,v)|^2$. Taking into account the above

considerations, the proposed neural network at the output has a module calculating power spectrum distribution (fig. 8).

For further calculations, only the real component will be used. This stage is indispensable for further data processing. Network response for the two-dimensional case is described by the equation:

$$y^{(u,v)} = \left(\frac{1}{MN} \left(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{(m,n)} w_{(m,n)}^{(u,v)re} + \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{(m,n)} w_{(m,n)}^{(u,v)im} \right) \right)^2 \quad (24)$$

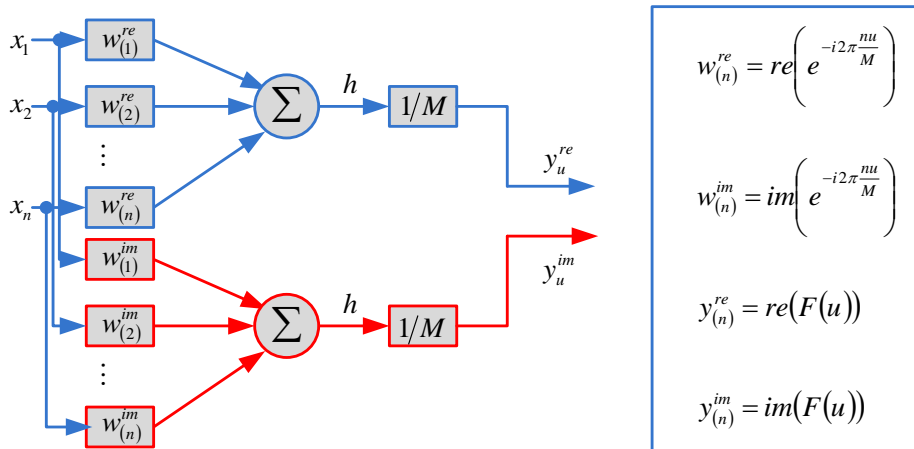


Fig. 7. Neuron calculating Fourier transform. Weights are calculated from the kernel of Fourier transform at the stage of network construction

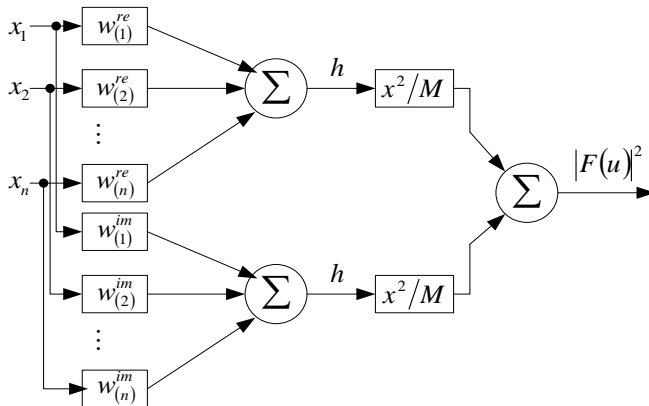


Fig. 8. Fourier neuron calculating power spectrum distribution of Fourier transform

3.2 Feature extractor in the form of a rectangular neural detector

The next stage in the digital system of diffraction pattern recognition is detection of the feature vector by a rectangular neural detector (RD). This process takes place in the input layer of the neural network. Each neuron of this layer is responsible for detection of one taught pattern. Therefore, the number of taught patterns is equivalent to the number of neurons in the input layer. The structure of the input layer neuron is similar to the structure of RWD (fig. 9). Each neuron of this layer has as many inputs as there are picture elements (pixels) of the image within Fourier plane. This plane is seen

by the neuron as a matrix of (ω, ϕ) coordinates (fig. 9)

In order to obtain the feature vector, neuron inputs must have a changed structure. It is a special case of an ordinary neuron. To obtain a structure equivalent to RWD, input connections are divided into sectors for which weights are identical. In the teaching process, all weights of a selected sector change in an identical way. Another important property of such a neuron is that during the teaching process, both the number of sectors as well as their mutual range can change (fig.10) (they do not overlap).

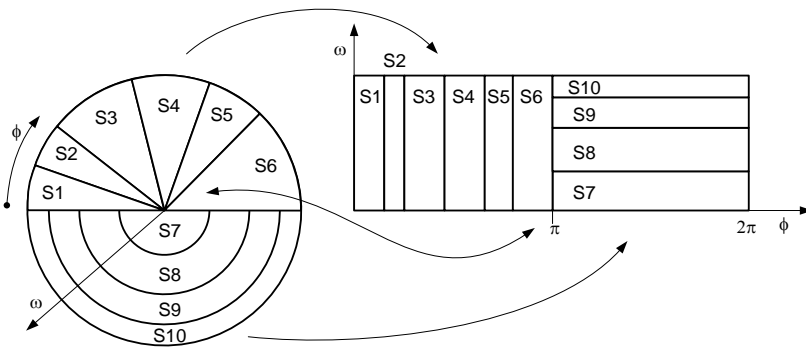


Fig. 9. Example of a feature extractor in the form of a matrix of ring-wedge detectors - RWD and its equivalent – rectangular detector – RD in the form of artificial neural network (ANNRD).

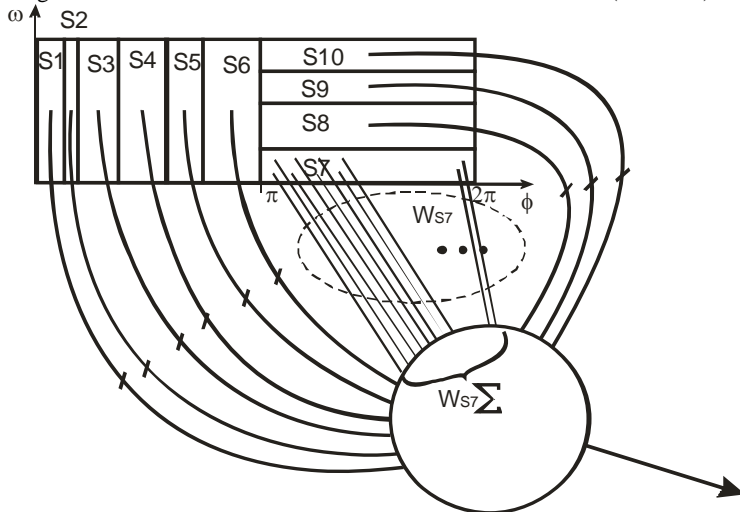


Fig. 10. A simplified diagram of a neuron adapted to play the function of RWD

Operation of rectangular detector (RD) has been illustrated on the example of the fragment of neuron where all elements of sector S7 (equivalent of the ring fig. 9) – are summed inside the neuron. Such a way of integrating of elements of all sectors reduces the image from Fourier plane to the vector of invariant features. This neuron plays one more important role. In the process of teaching, the weights change ($W_{S1}, W_{S2}, \dots, W_{S10}$). This property causes each neuron of the input layer to be sensitive to a different class of recognized objects. Each neuron of the input layer is taught by a different pattern and provides the network with a different feature vector. On this basis, the network makes decisions on pattern classification. The proposed network structures for further data processing are: network of type CP, ART, or networks taught by Grossberg or Kohonen method,

at the assumption that each of the proposed networks will be enriched by one additional input layer of the proposed structure.

It follows from the above considerations that the set of ring-wedge detectors has been implemented within the input layer of the neural network. This solution makes the construction of the whole system simpler without detriment to efficiency, and thanks to application as early as in the first stage spectral image processing by the artificial neural network, the system gains universality. This happens because it is capable of recognition of the number of object class equal with the number of input layer neurons. Simultaneously, optimality of particular detectors is kept. With the increase of possibilities, the system can be simplified to two blocks: the block of digital Fourier transform and the artificial neural network (fig. 11b)

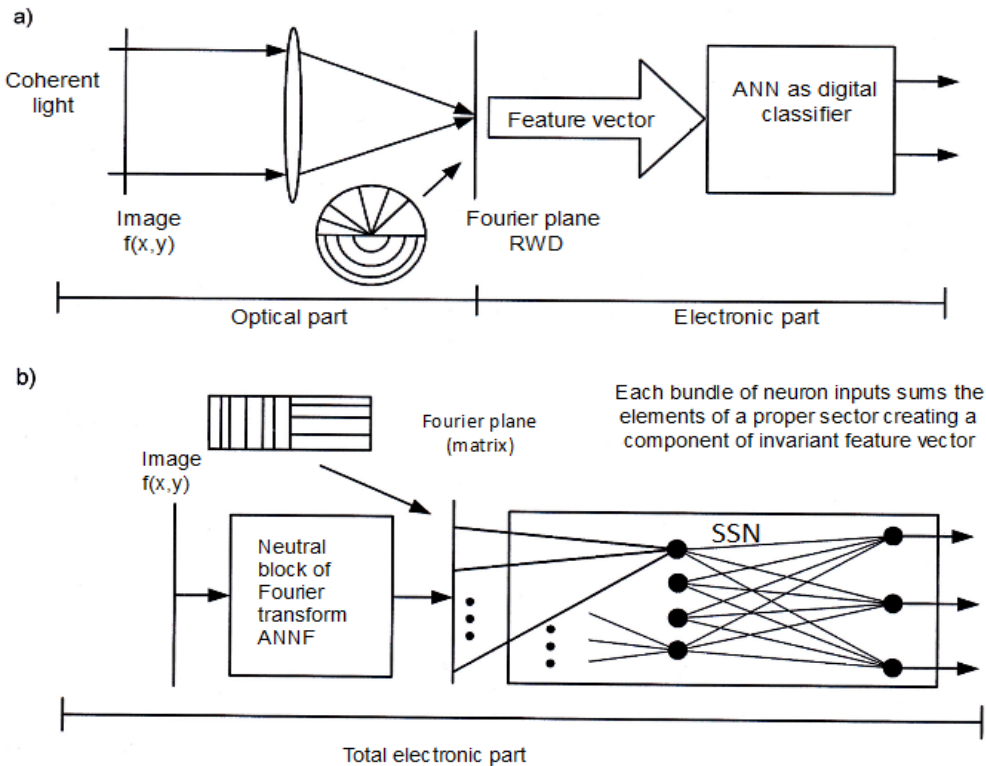


Fig. 11. Comparison of classic opto-electronic recognition system based on feature extractor in the form of RWD a) with the proposed totally digital electronic solution for the system b)

4. Synthesis of image data

The technique of combining information from many sources (image sensors) is at present a key problem with devices automatically making important decisions. A significant feature of this type of devices is automatic confirmation of the object by the synthesizing processor without the need of precise determining which sensors and which of their confidence levels should be engaged. Recently, data synthesis has become more and more appreciated, in particular image data synthesis. Data synthesis in the image domain is understood as combining data from various sources in order to obtain global knowledge about the recognized object. There are attempts at obtaining not only maximum knowledge about the location and geometry of the object but also at giving it appropriate significance.

Proposal [13] of the change of feature extractor in the form of a ring-wedge detector into diffraction gratings with variable refractive index in the form of a computer-generated hologram with areas in the shape of half-rings and wedges, divided light intensity integration (within diffraction gratings

areas) from light intensity conversion into electric signal (additional photodetector matrix). Computer-generated binary gratings contributed to a significant progress in the technology of cheap feature extractors for selected applications. This in turn made it possible to optimize the feature extractor with respect to the number and size of areas sampling a diffraction pattern.

Optimization methods based on the definition of object functions and evolution algorithms for classification space research were for the first time proposed in paper [13]. Characteristic features of diffraction patterns obtained by the optimized extractor constitute the input data for the classifier in the form of an artificial neural network.

In order to increase the probability of image recognition within diffraction space, image data synthesis is proposed (fig.12) from two spectral ranges (visible and infrared ranges). Combination of these two separate channels of information (characteristic features with the use of two independent extractors) is realized within the classifier based on the artificial neural network (ANN).

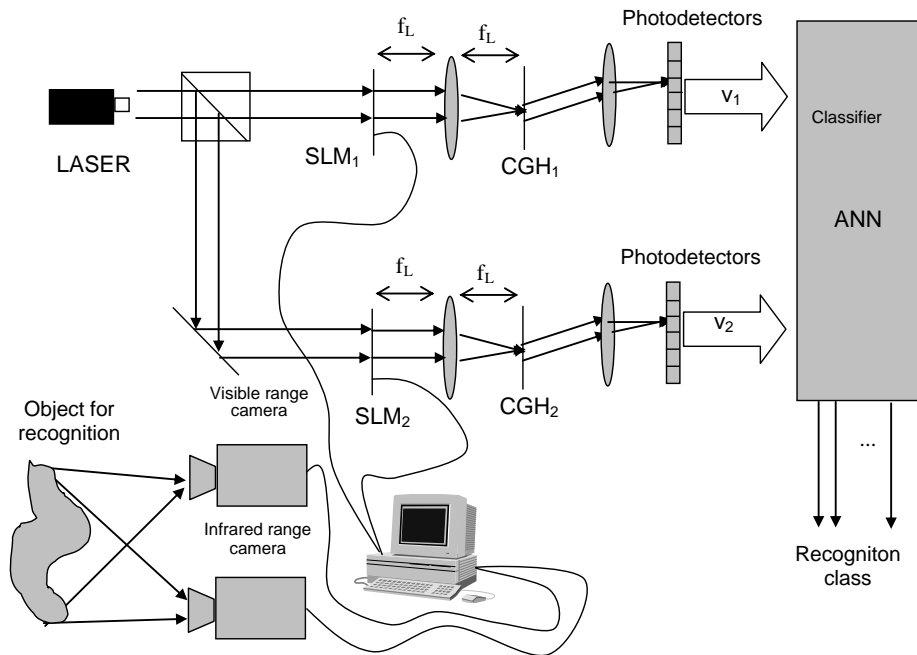


Fig. 12. Object recognition system within diffraction space with the data synthesis from two image sensors

The recognized object is within two spectral ranges. The image from the visible range is pictured (displayed) on the first spatial light modulator (SLM₁), whereas, the image from the infrared range is pictured on the second spatial light modulator (SLM₂). The two computer-generated holograms (CGH₁ and CGH₂) have the function of feature extractors – they generate two feature vectors (v_1 , v_2) (corresponding with two images of the same object). Detector matrices – photodetectors convert optical signals into electric signals. Feature vectors (discrete signals) constitute the input for the classifier.

5. Summary

Simple opto-electronic systems have been proposed for recognition of complex internal structure images, as well as a totally electronic system for image recognition within Fourier plane, which can be easily realized in a program version. Image data synthesis within diffraction plane significantly increases the probability of system detection with moderately high probabilities of a false alarm of image sensors. The conducted experiments indicated high efficiency of diffraction systems recognition (several per cent of normalized decision error has been obtained).

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