MOTION ANALYSIS BASED ON INVERTIBLE RAPID TRANSFORM

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Abstract

This paper presents the results of a study on the use of invertible rapid transform (IRT) for the motion estimation in a sequence of images. Motion estimation algorithms based on the analysis of the matrix of states (produced in the IRT calculation) are described. The new method was used experimentally to estimate crowd and traffic motion from the image data sequences captured at railway stations and at high ways in large cities. The motion vectors may be used to devise a polar plot (showing velocity magnitude and direction) for moving objects where the dominant motion tendency can be seen. The experimental results of comparison of the new motion estimation methods with other well known block matching methods (full search, 2D-log, method based on conventional (cross correlation (CC) function or phase correlation (PC) function) for application of crowd motion estimation are also presented.

Keywords

motion estimation, rapid transform, invertible rapid transform

1. Introduction

The rapid transform (RT) [13] is a fast shift invariant transform. The RT is useful for pattern recognition, if the position of the pattern is unknown or the pattern is moving [1, 19 ,20].

However, the RT eliminates non only knowledge about position but also a lot of information about the original pattern itself. Generally it is not possible to obtain the original pattern, only from its RT [13]. In [3, 6, 18] was introduced that exists an invertible fast shift invariant transform based on the RT. This transform (invertible rapid transform (IRT)) consists of an RT which supplies a shift invariant pattern from the input pattern and a binary coding process (generating additional data) which records the "phase-information" of the input pattern. Thus additional data are known as a matrix of states (binary matrix) for 1D-IRT or system of matrices of states (system of binary matrices) for 2D-IRT [18].

The proposed motion estimation algorithms [5, 8, 9, 10, 17] are based on the presumption that in matrix of states or in system of matrices of states is included relevant information about an image. Cyclical translations in the image are deterministicaly and unambiguously encoded to the values of this matrix or system of matrices. These matrices may be computed with use of simple and very fast algorithm using operation of comparison, addition and subtraction [18].

At the proposed paper the methods and results of motion estimation based on using matrix of states or system of matrices of states will be described. The experimental results of these methods are compared with the results obtained by the well-known 2D-log method in real image sequences.

2. Rapid transform (RT)

RT is a member of the class CT (certain transforms - fast translation invariant transforms) [23]. The transforms of the class CT can be divided according to the employed functions $f_s(a,b)$, (s=1,2) [19, 23]. The RT was introduced by Reitboeck and Brody [13] for application in pattern recognition.

The RT results from a simple modification of the Walsh-Hadamard transform (WHT). The signal flow graph for the RT is identical to that of WHT (Fig.1), except that the absolute value of the output of each stage of the iteration is taken before feeding it to the next stage. This is not an orthogonal transform, as no inverse exists. RT has some interesting properties such as invariance to cyclic shift, reflection of the data sequence, and slight rotation of two-dimensional patterns. Various properties of RT have been developed in [1]. RT was used in recognition of alphanumeric characters [1, 12, 13, 24], robotics [19] and scene analysis [14]. More recently the modified rapid transform (MRT) [4] was presented to break undesired invariance of the RT, which leads to a loss of information about the original pattern. MRT was used in pattern recognition [4, 21] and in recognition of 3D objects [15]. In the following we will quickly review the RT.

Let us consider samples of one-dimensional signal represented as vector

$$\overline{\mathbf{X}} = \{x(i)\};\ i = 0,1, \ldots, N\text{-}1 \quad N = 2n \qquad (1)$$

and samples of two-dimensional signal represented as matrix

$$[\mathbf{X}] = \{x(i,j)\};\ i,j = 0, 1, \ldots, N\text{-}1 \quad N = 2^n. \qquad (2)$$

In general transform data in step **r** are computed from data from step **r-1** with use of recurrent formula.

For one-dimensional signal

$$x(i+2js)^{(r)} = \left|x(i+2js)^{(r-1)} + x\left[i+(2j+1)s\right]^{(r-1)}\right|$$

$$x\left[i+(2j+1)s\right]^{(r)} = \left|x(i+2js)^{(r-1)} - x\left[i+(2j+1)s\right]^{(r-1)}\right| \qquad (3)$$

where $i = 0,1, \ldots, s\text{-}1$,

$j = 0,1, \ldots, t\text{-}1$,

$r = 1, 2, \ldots, n$,

$s = 2^{n-r}$, $t = 2^{r-1}$

n is the number of needed transform steps.

For two-dimensional signal

$$x(2i,2j)^{(r)} = \Big\|x(i,j)^{(r-1)} + x(i+N/2,j)^{(r-1)}\Big| + \Big|x(i,j+N/2)^{(r-1)} + x(i+N/2,j+N/2)^{(r-1)}\Big\|$$

$$x(2i+1,j)^{(r)} = \Big\|x(i,j)^{(r-1)} - x(i+N/2,j)^{(r-1)}\Big| + \Big|x(i,j+N/2)^{(r-1)} - x(i+N/2,j+N/2)^{(r-1)}\Big\|$$

$$x(2i.2j+1)^{(r)} = \Big\|x(i,j)^{(r-1)} + x(i+N/2,j)^{(r-1)}\Big| - \Big|x(i,j+N/2)^{(r-1)} + x(i+N/2,j+N/2)^{(r-1)}\Big\|$$

$$x(2i+1.2j+1)^{(r)} = \Big\|x(i,j)^{(r-1)} - x(i+N/2,j)^{(r-1)}\Big| - \Big|x(i,j+N/2)^{(r-1)} - x(i+N/2,j+N/2)^{(r-1)}\Big\| \qquad (4)$$

where $i, j = 0,1, \ldots, (N/2\text{-}1)$,

$r = 0,1, \ldots, n$

n is the number of needed transform steps.

3. Invertible rapid transform (IRT)

Even if RT is non-linear and thus non-invertible, by generating an additional data that indicates which pixel of an operand is greater during the forward RT, one can perform uniquely the invertible RT (IRT) [6, 18]. Thus additional data are known as a matrix of states $\boldsymbol{K}$ (binary matrix) for 1D-RT or system of matrices of states $\boldsymbol{K}_p^{(r)}$ (system of binary matrices) for 2D-RT. Signal flow graph for compute of the 1D IRT [18] is shown in Fig.1.

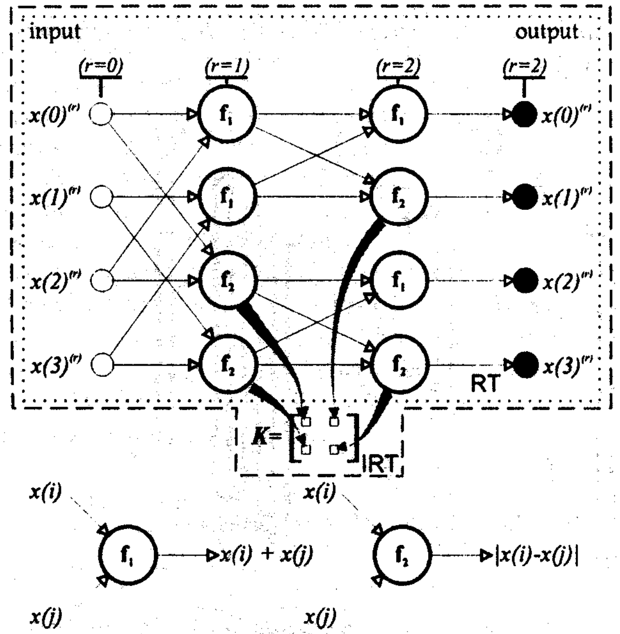


Fig.1 Signal flow graph of the 1D IRT

The matrix of states $\boldsymbol{K}$ or system matrices of states $\boldsymbol{K}_p^{(r)}$ may be computed as follows. For one dimensional case:

$$k(i,r) = 0, \text{ if } x(i)^{(r)} - x(i+N/2)^{(r)} < 0$$

$$k(i,r) = 1, \text{ if } x(i)^{(r)} - x(i+N/2)^{(r)} \geq 0. \qquad (5)$$

The dimension of matrix $\boldsymbol{K}$ is $n \times N/2$. For two dimensional case:

$$k_1^{(r)}(i,j) = 1, \text{ if } x^{(r)}(i,j) - x^{(r)}(i+N/2,j) \geq 0$$

$$k_1^{(r)}(i,j) = 0, \text{ if } x^{(r)}(i,j) - x^{(r)}(i+N/2,j) < 0$$

$$k_2^{(r)}(i,j) = 1, \text{ if } x^{(r)}(i,j+N/2) - x^{(r)}(i+N/2,j+N/2) \geq 0$$

$$k_2^{(r)}(i,j) = 0, \text{ if } x^{(r)}(i,j+N/2) - x^{(r)}(i+N/2,j+N/2) < 0$$

$$k_3^{(r)}(i,j) = 1, \text{ if } x^{(r)}(i,j) - x^{(r)}(i+N/2,j) \geq 0$$

$$k_3^{(r)}(i,j) = 0, \text{ if } x^{(r)}(i,j) - x^{(r)}(i+N/2,j) < 0$$

$$k_4^{(r)}(i,j) = 1, \text{ if } x^{(r)}(i,j+N/2) - x^{(r)}(i+N/2,j+N/2) \geq 0$$

$$k_4^{(r)}(i,j) = 0, \text{ if } x^{(r)}(i,j+N/2) - x^{(r)}(i+N/2,j+N/2) < 0 \qquad (6)$$

where (r) is transform step of IRT and

$i, j = 0,1, \ldots, (N/2\text{-}1)$

$r = 1, 2, \ldots, n$

$p = 1, 2, 3, 4$

The system of matrices of states $K_p^{(r)}$ is illustrated in Fig.2.

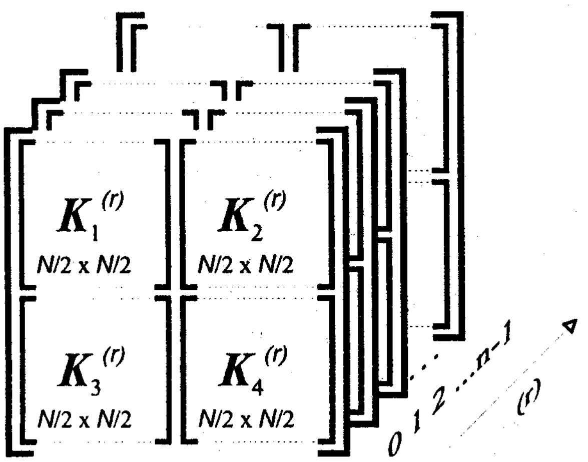


Fig.2 The system of matrices of states $K_p^{(r)}$

4. Motion estimation algorithms with use of IRT

This motion estimation algorithms are based on presumption that in matrix K or in system $K_p^{(r)}$ is included relevant information about the picture [1, 10, 17, 18, 19, 20] and the motion in picture influence the first column of K or the first set of matrices of $K_p^{(r)}$ (i.e. $K_1^{(0)}, K_2^{(0)} K_3^{(0)}, K_4^{(0)}$) in maximal way.

First, the image is divided into smaller rectangular areas, which we call subblocks (See Fig.3). Let U_q be an N x N size subblock of frame **q** and U_{q-1} be equivalent subblock of frame **q-1**. Let search area (SA) be an $(N+2d_m)$ x $(N+2d_m)$ size of frame **q-1**, centred at the same spatial location as U_q and U_{q-1} is subblock from SA, where d_m is the maximum displacement allowed in either direction in integer number of pixel.

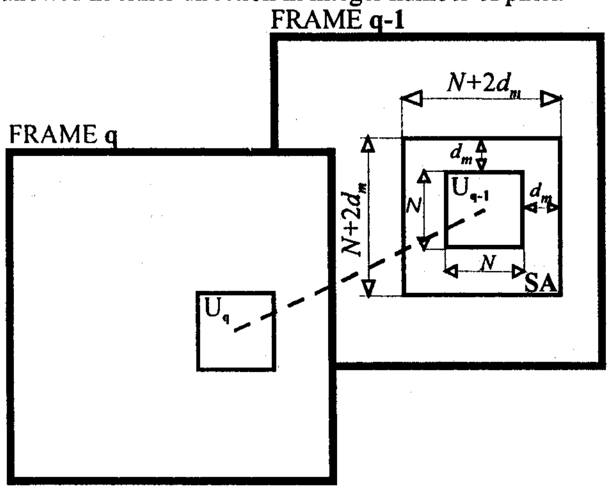


Fig.3 Positions of subblocks $U_{q(q-1)}$ and SA at the frames q (q-1)

4.1 Motion estimation algorithms with use of 1D-IRT

Let K_r and K_c are matrices of states computed by row and by column of subblock respectively.

__STEP 1:__ Compute $K_{r(q)}$, $K_{c(q)}$ for subblock U_q.

__STEP 2:__ Compute $K_{r(q-1)}$, $K_{c(q-1)}$ for subblock U_{q-1}.

__STEP 3:__ Compute matching criterion

$$\sigma_{row}(u,v)=\sum_{r=0}^{N-1}\sum_{i=0}^{N/2-1}\sum_{j=0}^{\mu}\left(k_{r(k)}(i,j)\oplus k_{r(k-1)}(i,j)\right)$$

$$\sigma_{col}(u,v)=\sum_{r=0}^{N-1}\sum_{i=0}^{N/2-1}\sum_{j=0}^{\mu}\left(k_{c(k)}(i,j)\oplus k_{c(k-1)}(i,j)\right).$$

$$u,v\in\langle -d_m, d_m\rangle \tag{7}$$

Repeat steps 2, 3 for every possible positions (u,v) of subblock U_{q-1} in subblock SA ($(2d_m+1)^2$ cycles), where $\oplus$ denotes bit-by-bit modulo 2 addition.

__STEP 4:__ The desired vector of motion correspond to the position (u_0, v_0) of subblock U_{q-1} with minimal value of $\sigma(u, v)$.

__Modifications of the algorithm - I__

μ -number of used columns of matrix K

$\mu\in\{0, 1, ..., n-1\}$

__Modifications of the algorithm - II__

$4a,\ (u_0,v_0)\in\{u,v\};\sigma_{row}(u_0,v_0)=\min(\sigma_{row}(u,v))$

$4b,\ (u_0,v_0)\in\{u,v\};\sigma_{col}(u_0,v_0)=\min(\sigma_{col}(u,v))$

$4c,\ (u_0,v_0)\in\{u,v\};\sigma_{row}(u_0,v_x)=\min(\sigma_{row}(u,v))\wedge$
$\wedge\ \sigma_{col}(u_x,v_0)=\min(\sigma_{col}(u,v))$

$4d,\ (u_0,v_0)\in\{u,v\};\sigma_{r+c}(u_0,v_0)=\min(\sigma_{r+c}(u,v)),$ (8)

where $\sigma_{r+c}(u,v)=\sigma_{row}(u,v)+\sigma_{col}(u,v)$ (9)

4.2 Motion estimation algorithm with use of 2D-IRT

__STEP 1:__ Compute first set of $K_p^{(r)}$ (i.e. $K_{1(q)}^{(0)}, K_{2(q)}^{(0)}, K_{3(q)}^{(0)}, K_{4(q)}^{(0)}$) for block U_q.

__STEP 2:__ Compute first set of $K_p^{(r)}$ (i.e. $K_{1(q-1)}^{(0)}, K_{2(q-1)}^{(0)}, K_{3(q-1)}^{(0)}, K_{4(q-1)}^{(0)}$) for block U_{q-1}.

__STEP 3:__ Compute matching criterion

$$\sigma(u,v)=\sum_{p=1}^{\tau}\sum_{i=0}^{N/2-1}\sum_{j=0}^{N/2-1}\left(k_{p(q)}^{(0)}(i,j)\oplus k_{p(q-1)}^{(0)}(i,j)\right)$$

$$u,v\in\langle -d_m, d_m\rangle \tag{10}$$

Repeat steps 2, 3 for every possible positions (u,v) of subblock U_{q-1} in subblock **SA** ($(2d_m+1)^2$ cycles), where $\oplus$ denotes bit-by-bit modulo 2 addition.

Modifications of the algorithm

3a, $\tau = 1$ (K1)

3b, $\tau = 2$ (K1, K2)

3c, $\tau = 3$ (K1, K2, K3)

3d, $\tau = 4$ (K1, K2, K3, K4)

STEP 4: The desired vector of motion corresponds to the position (u_0,v_0) of subblock U_{q-1} with minimal value of $\sigma(u, v)$, i.e.

$$\left(u_0,v_0\right) \in \{u,v\};\sigma\left(u_0,v_0\right) = \min\left(\sigma(u,v)\right) \quad (11)$$

5. Experiments and results

The new algorithms of motion estimation was experimentally verified in various applications [9, 16, 17]. The methods mentioned above was simulated on personal computer. The results was found using a frames of 256 x 256 pixels quantized uniformly to 8 bits.

5.1 Crowd and object motion estimation

The understanding of moving objects behavior in semi-confined spaces is an important part of the design of new pedestrian facilities and major layout modifications to existing areas and, for the daily management of objects movement in and out a large cities is a substantial problem with serious consequences for human life and safety for public order if it is not managed successfully [2].

Human observers can detect many features of moving objects, in some cases quite easily. Normally they can distinguish between a moving and a stationary objects and estimate the majority direction and speed of movement of the objects. For facilities already in existence, there is an established practice of using extensive closed circuit television monitoring of moving objects. Human observers normally positioned to watch the TV monitors of a such systems are not sufficient for obtain real time data by watching recorded video sequences. There is thus a considerable benefit from being able to develop methods for automatically collecting moving objects description data by use of image processing techniques applied to the video sequences [2]. These methods are based on well established image processing techniques and are able to monitoring and collecting data about key features of objects: stationarity, density and motion.

The new method of motion estimation was used to estimate crowd and traffic motion from the image data sequences captured at highways and at railway stations in large cities [16, 22]. The block scheme of the proposed object motion estimator is shown in Fig.4. For subsequent image frames the subblocks displacement vectors was calculated (Fig.5a). Then the vectors was used to devise a polar plot (showing velocity magnitude v and direction s) for moving crowd and traffic, with use of their aggregation to discrete direction 'bins' and with various bin size (Fig.5 b, c). From these polar histograms the dominant motion tendency of the motion crowd and traffic may be clearly identified. Localized variations of brightness cause errors in the computed motion vectors compared to the actual overall motion of the individuals in the crowd. This effect can be easily removed (filtered) from these polar diagrams (Fig.5c). The proposed experiments indicate that **IRT** motion estimation gives good results in terms of computation cost, speed and motion estimation.

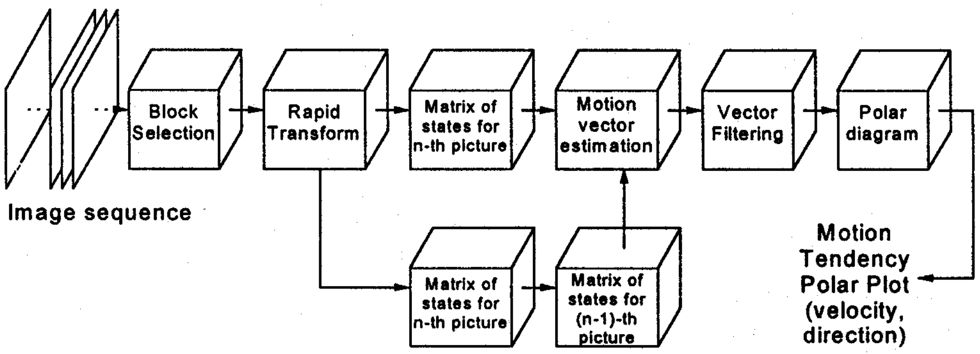
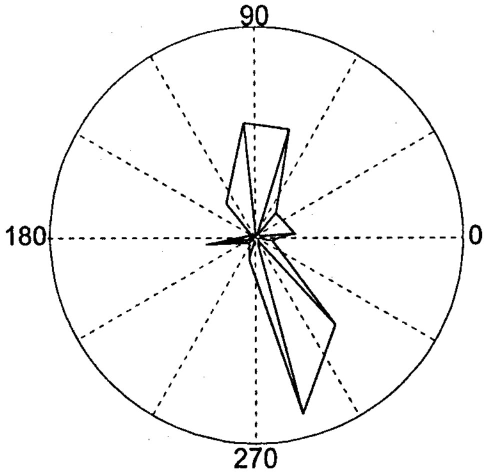
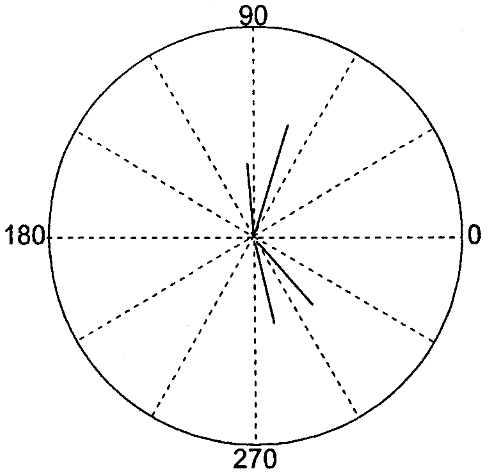


Fig.4 Block scheme of the object motion estimator

a)



b)



c)

Fig.5 Motion estimation with use of the 2DIRT: a) frame from the image sequence „ Liverpool railway station in London" with motion vectors, b) polar diagram of the motion direction, c) polar diagram of the motion direction and velocity after undesirable motion filtration

5.2 Comparison with Other Method

Particular estimation of crowd motion is based on two well known methods: optical flow and motion estimation. Various methods of motion estimation have been developed and described in the literature [11]. Most of these techniques are based on the assumption of purely translation displacement of objects with no change of shape or grayvalue with time.

An efficient technique is the well known block matching method. For the estimation of the displacement vector (u_0, v_0) in a point (x, y) in frame **q**, a small matching block centered at point (x, y) is taken from frame **q** and compared with all matching blocks centered at points $(x-u, y-v)$ within a searching area of frame **q-1**; the best match is taken as the presumable displacement vector. Typical (usually used) matching criterion are mean-square error (MSE) defined as

$$MSE(u,v) = \frac{1}{M.N} \sum_{m=1}^{M} \sum_{n=1}^{N} \left[X_q(m,n) - X_{q-1}(m+u, n+v) \right]^2 \tag{11}$$

or mean-absolute difference (MAD) defined as

$$MAD(u,v) = \frac{1}{M.N} \sum_{m=1}^{M} \sum_{n=1}^{N} \left| X_q(m,n) - X_{q-1}(m+u, n+v) \right| \tag{12}$$

where X_q, (X_{q-1}) are picture elements of matching block of frames **q**; **(q-1)**, size of matching block is M by N. Assuming a maximum horizontal or vertical displacement of d_m picture elements $(-d_m \le u,\ v \le d_m)$.

The full search procedure for finding the correlation peak requires an evaluation of MSE or MAD at

$$Q = (2d_m + 1)^2 \tag{13}$$

different horizontal and vertical shifts.

In order to reduce computational cost by reducing the high amount of trials, several fast search algorithms for block matching have been developed (2D-log, 3-step, conjugate direction search methods etc.) [11]. In these methods, the best match of the first step is the starting point of the subsequent step in which the search points are less coarsely spaced.

Another very promising method is block matching with use of the conventional (cross) correlation (CC) function or phase correlation (PC) function [7]. The CC function of two blocks of frames **q** and **q-1** is defined as

$$R_{q,q-1}(m,n) = \mathcal{F}^{-1}\left\{ \mathcal{F}^{*}\left[X_q(m,n)\right] . \mathcal{F}\left[X_{q-1}(m,n)\right] \right\} \tag{14}$$

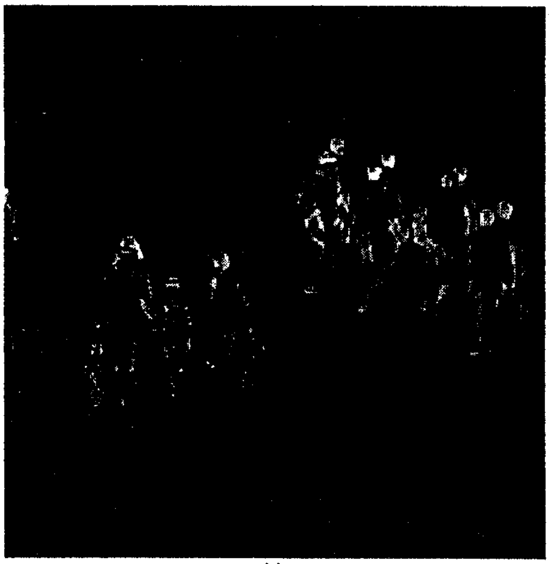
and PC function is defined as

$$\Phi_{q,q-1}(m,n) = \mathcal{F}^{-1}\left\{ \frac{\mathcal{F}^{*}\left[X_q(m,n)\right] . \mathcal{F}\left[X_{q-1}(m,n)\right]}{\left| \mathcal{F}^{*}\left[X_q(m,n)\right] . \mathcal{F}\left[X_{q-1}(m,n)\right] \right|} \right\} \tag{15}$$

where $\mathcal{F}$ denotes operator of the fast Fourier transform and * is the symbol of the conjugation. PC function in contrast to the CC function exhibits an extremely narrow correlation peak for translation motion [7].

The new methods of motion estimation was used to estimate crowd motion from the image data sequences captured at railway stations in large cities and compared with results obtained by using of full search method, 2D-log method (with *MAD* criterion), CC method and PC method. For subsequent image frames (Fig.6) the subblock displacement vectors using methods mentioned above were calculated. Then the vectors was used to devise a polar plot (showing velocity magnitude m and direction d) for moving crowd, with use of their aggregation to discrete directions „bins" and with various bin size (Fig.7.a-f). The all space was quantized to various numbers discrete angles theta and all motion vectors from this angle was cumulated to one bin. From these polar histograms the dominant motion tendency of the motion crowd can be clearly determined. For all method: block size =16 pel; d_m = 10 pel; theta = 10°. The obtained results are compared in tab.1.

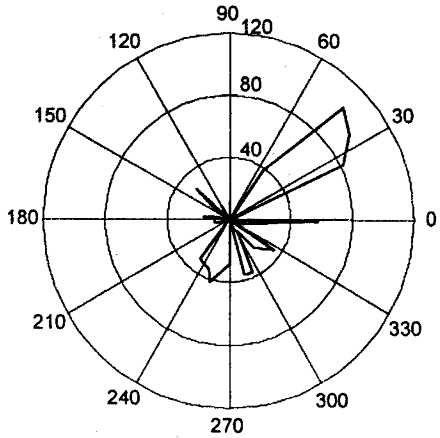
a)



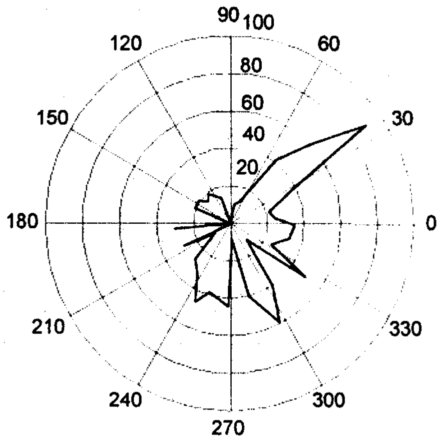
b)

c)

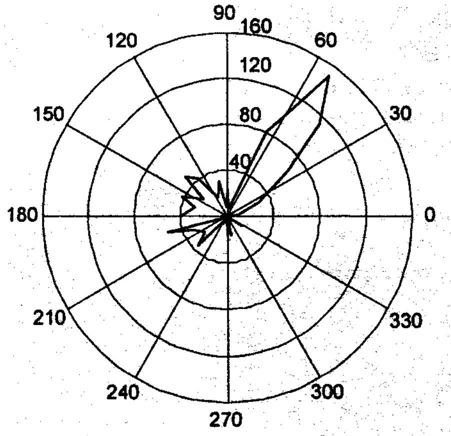
Fig.6 The image frame (a-b), difference of subsequent frames (b) and found motion vectors by use motion estimation method based on 1D-IRT (c from railway station in Košice



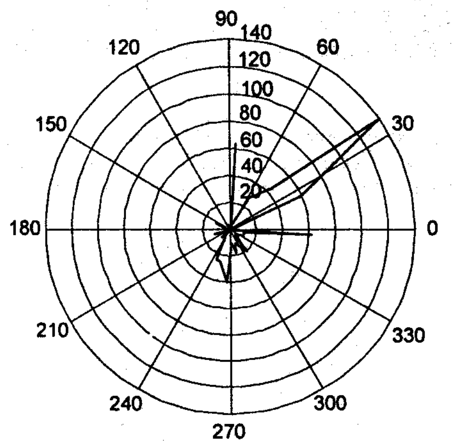
a)



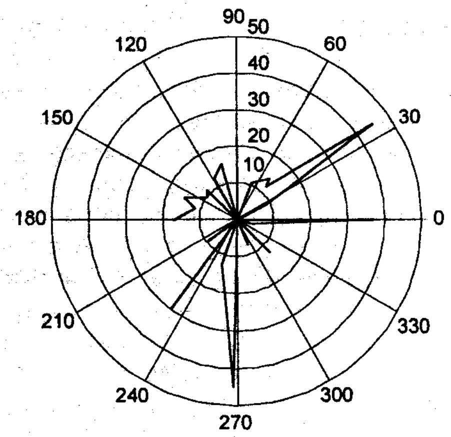
b)



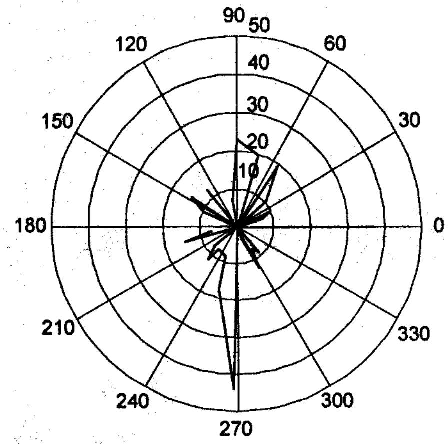
c)



d)



e)



f)

Fig. 7 Polar plot *m-d* by use of motion estimation: a) based on 1D-IRT, b) based on 2D-IRT, c)full search, d) 2D-log method, e) based on CC, f) based on PC.

Tab.1

MOTION ESTIMATION METHODS COMPARATIVE TABLE							
		Angle [degrees]					
		30 - 60	240 - 270	270 - 300	300 - 330		
	Number of blocks	46	10	8	6		
	Size of movement vector [pel]	8	6	7	9	Euclide distance	Correl. coef.
Magnitude	Theoretical	368	60	56	54		
	1D IRT	236	103	73	67	**19731**	**0,9830**
	2D IRT	192	128	108	102	40608	**0,9671**
	Full search	328	27	17	16	**5654**	**0,9999**
	2D log	210	89	39	40	**26290**	0,9612
	CC	70	57	8	13	92798	0,7171
	PC	30	70	16	16	117388	-0,0632

6. Conclusion

The proposed experiment results indicate that IRT motion estimation gives good results in terms of computation cost, speed and motion estimation accuracy. The found movement vectors and polar plots are more realistic (with comparison to real interframe movement) for 1D and 2D-IRT methods like for CC and PC methods.

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