DIFFUSION BACKGROUND MODEL FOR MOVING OBJECTS DETECTION

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ABSTRACT:

In this paper, we propose a new approach for moving objects detection in video surveillance systems. It is based on construction of the regression diffusion maps for the image sequence. This approach is completely different from the state of the art approaches. We show that the motion analysis method, based on diffusion maps, allows objects that move with different speed or even stop for a short while to be uniformly detected. We show that proposed model is comparable to the most popular modern background models. We also show several ways of speeding up diffusion maps algorithm itself.

1. INTRODUCTION

Recently a lot of background models intended for moving object detection and foreground segmentation were introduced. Moreover, changedetection.net benchmark was created (Goyette, 2012, Y. Wang, 2014) for testing and ranking existing and new algorithms for change and motion detection.
In the paper (Vishnyakov, 2012) we introduced the regression pseudospectrum background model, that was based on the fast way of accumulating the layers of the spectrum using the regression model. However, despite the very high computation speed, that approach lacked quality in complex conditions (swaying branches, changeable lighting conditions, slow objects).
The idea of our new approach is as follows: we improve regression background model using diffusion maps and diffusion regressive filtering.
Below in this paper we describe our approach and provide evaluation results on the changedetection.net database for the most suitable categories: «baseline», «thermal», «bad weather», «low framerate».

2. DIFFUSION BACKGROUND MODEL

2.1 Diffusion map

Let $I(k)$ be the input image on the frame k. Let us assume that $I(k)$ is a grayscale image (or it has been converted to grayscale), $I(k,q)$ is the brightness value of the image I in pixel q.
The basis of our approach is the diffusion morphology (Vizilter, 2013) which allows comparing images by shape matching using the projection of image one on image two. In this morphology the projection is evaluated using diffusion maps, that were introduced in (Lafon, 2004, Coifman, 2006a, Coifman, 2006b):

$$P_{I_2}^{I}(k,p) = \sum_q A_{p,q}(k) I_2(q),$$

where p, q – points,
$A_{p,q}(k) = \frac{\exp\left(-\frac{\|v(p)-v(q)\|^2}{\varepsilon}\right)}{\sum_q \exp\left(-\frac{\|v(p)-v(q)\|^2}{\varepsilon}\right)}$ – a diffusion operator (diffusion map),
$v(p)$ – a feature vector, calculated in the point p of the image I with the square kernel,
$\|\cdot\|$ – a distance between two feature vectors.

2.2 Complex LBP Descriptor

In the papers (Gorbatsevich, 2014, Vishnyakov, 2014) the complex LBP descriptor was introduced as a feature vector $v(\cdot)$ along with the hamming distance $\|\cdot\|$ as a distance between feature vectors for the diffusion maps. This allows very fast computation of the diffusion map.
Our implementation provides a possibility for real time image processing. The computation of diffusion filtering with heat kernel in its original form is an extremely time-consuming procedure even for reasonable neighbourhood of p. We propose to substitute such computationally unpleasant descriptors by the combination of intensity $I(p)$ and threshold LBP (Ahonen, 2004) for $v(p)$. In our experiments, the mean value of intensity in the p neighbour was used. Mean value is computed by a fast algorithm with sliding sum recalculation (but this is not presented in code below). The local binary pattern (LBP) is calculated as a 64-bit vector for each pixel p based on a comparison of its value and values of its neighbours in sliding window. If the value of neighbour pixel is less than the value of central pixel and the difference between them is greater than threshold, then the corresponding bit is set to 1, otherwise – to 0. We substitute the original neighbourhood matching metrics by LBP matching metric - Hamming distance, the mean values of intensities are compared by threshold. As local binary patterns are stored as bit fields, the computation of Hamming distance is performed via bitwise XOR operation. The exponent is calculated using table values. Due to this, the usage of our complex LBP descriptor allows both increasing the computational speed and obtaining heat kernels very similar to original.

2.3 Background model

The idea of the paper is as follows: the approach for the image comparison in the diffusion morphology can be also used for the moving object detection. For robustness of the approach we propose regression accumulators (Vishnyakov, 2012) $m_n(k)$ and $m_n^*(k)$ for both the original image and the filtered image respectively:

$$m_n(k) = \alpha \cdot m_n(k-1) + (1-\alpha) \cdot I(k),$$
$$m_n^*(k) = \alpha \cdot m_n^*(k-1) + (1-\alpha) \cdot I^*(k),$$

where $I^*(k) = P^{I(k)}_{m_n(k)}(k)$ is a diffusion filter of the $I(k)$, which is the projection of $I(k)$ on the memory $m_n(k)$, n is a parameter, related to the memory length, $\alpha = \alpha(n)$.
After computing $m_n(k)$ and $m_n^*(k)$, we compare the difference

$$D(k) = |m_n^*(k) - I^*(k)|$$

to the threshold in each pixel and get the binary moving object mask $M(k)$:

$$M(k) = \begin{cases} 1, D(k) \geq thr \\ 0, D(k) < thr \end{cases}.$$

2.4 Illustrations

On figure 1 we show smoothed accumulator (memory) $m_n^*(k)$ using regression model for the projection image $I^*(k)$ – a diffusion filter of the $I(k)$. As you can see, no moving object is present on this accumulator. In addition, the accumulator is smoothed because of smoothing properties of the diffusion map.
On figure 2 we show the projection image $I^*(k)$ itself. One moving object is present on this image. The projection image is also smoothed.
On figure 3 we show the difference $D(k)$ between projection image $I^*(k)$ and smoothed accumulator $m_n^*(k)$.
On figure 4 we show image $M(k)$ – binarized using threshold difference image $D(k)$.

Figure 1. Smoothed memory $m_n^*(k)$.

Figure 2. Image projection $I^*(k)$.

Figure 3. Background difference $D(k)$.

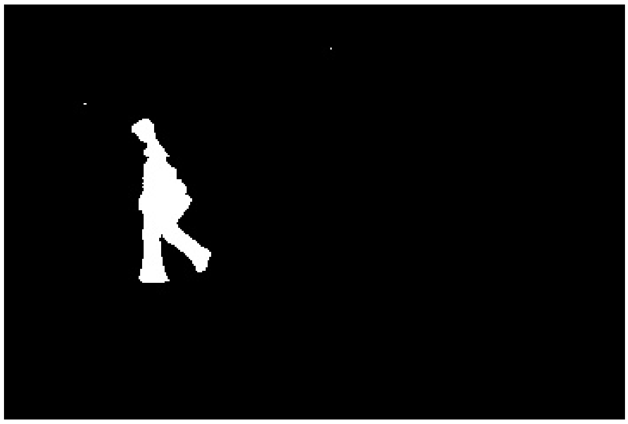

Figure 4. Binarized background difference $M(k)$.

EXPERIMENTS

In order to demonstrate the quality characteristics of the proposed approach we use the common benchmark videos from changedetection.net database (changedetection.net, 2014). Changedetection.net provide a realistic, camera-captured, diverse set of 31 videos (~70,000 frames). They have been selected to cover a wide range of detection challenges and are representative of typical indoor and outdoor visual data captured today in surveillance, smart environment and video database scenarios. The 2014 dataset consist of different categories. We choose «baseline», «thermal», «bad weather», «low framerate» categories, because the proposed approach can be directly applicable to them in the presented straightforward form (regression model of background learning). Other «camera jitter», «shadow», «PTZ» (pan-tilt zoom) scenarios are not considered, because they require some special modification of the basic algorithm, we hope to explore them in the future.
«Baseline» category represents a mixture of moderate challenges. Some videos have subtle background motion, others have isolated shadows, some have an abandoned object and others have pedestrians that stop for a short while and then move away. «Thermal» category includes videos that have been captured by far-infrared cameras. These videos contain typical thermal artifacts such as heat stamps (e.g., bright spots left on a seat after a person gets up and leaves), heat reflection on floors and windows, and camouflage effects, when a moving object has the same temperature as the surrounding regions. «Bad Weather» category includes outdoor videos captured in challenging winter weather conditions, i.e., snow storm, snow on the ground, fog. «Low Frame-Rate» category contains videos capture at varying frame-rates between 0.17 fps and 1 fps. For «baseline» and «thermal» categories the results of proposed

approach was compared to 37 other existed methods results available from change detection 2012 benchmark. For «Bad Weather», «Low Frame-Rate» categories the results of proposed approach was compared to 22 other existed methods results available from change detection 2014 benchmark.
The following methods were used for comparative analysis: SUBS (St-Charles, 2014), PAWCS (St-Charles, 2015), SOBS1 (L. Maddalena, 2012), SOBS2 (L. Maddalena, 2010), SOBS3 (L. Maddalena, 2008), PSP (A. Schick, 2012), S-360_1 (M. Sedky, 2011), MLBS (Jian Yao, 2007), GPGMM (T. S. F. Haines, 2012), SGMM (R. Heras, 2011), PBAS2 (M. Hofmann, 2012), KDE1 (A. Elgammal, 2000), BB (F. Porikli, 2005), CDPS (Francisco J. Hernandez, 2013), HIST (J. Zheng, 2006), CWD (M. De Gregorio, 2013), KNN (Z. Zivkovic, 2006), GMM1 (P. KaewTraKulPong, 2001), MAHAL (Y. Benezeth, 2010), CHEB1 (A. Morde, 2012), RMOG (S. Varadarajan, 2013), LSS (J-P Jodoin, 2012), GMM2 (Z. Zivkovic, 2004), ED (Y. Benezeth, 2010), GMM3 (D. Riahi, 2012), SGMM (Heras Evangelio, 2012), UBA (D. Park, 2009), PROST (F. Seidel, 2014), GMM4 (C. Stauffer, 1999) TUBI (L. Dar-Shyang, 2005), KDE2 (Y. Nonaka, 2012), KDE3 (S. Yoshinaga, 2013), QCHMD (O. Strauss, 2012), CHEB2 (A. Morde, 2012), FTSG (R. Wang, 2014), SS (Zhenkun, 2015), BWA (B. Wang, 2014), EFIC (G. Allebosch, 2015), S-360_2 (M.Sedky,2014), CWDH (M. De Gregorio, 2014), UBSS (H. Sajid, 2015), MSTBGM (Xiqun Lu, 2014).

Quantitative results for «baseline» category are shown in Tables 1, 2, 3. The following metrics are used: Re – Recall, SP - (Specificity), FPR - False Positive Rate, FNR - False Negative Rate, PWC - Percentage of Wrong Classifications, F - F-Measure, PR – Precision, TP - True Positive, FP - False Positive, FN - False Negative, TN - True Negative, Rank – rank among all comparative methods in chosen category (38 or 22).

DIFF	TP	FP	FN	TN
pedestrians	619693	122498	51169	67446609
PETS2006	2915070	295655	1913120	366417649
highway	4728297	1220961	729692	85433508
office	7932008	303147	710086	116235539
baseline	*16195068*	*1942261*	*3404067*	*635533305*

Table 1. Baseline category. Results for each video in this category.

Method	RE	SP	FPR	FNR	PWC	F	PR
SUBS	0,95	0,99	0,002	0,05	0,35	0,95	0,94
PAWCS	0,94	0,99	0,002	0,05	0,44	0,93	0,93
SOBS1	0,93	0,99	0,002	0,06	0,37	0,93	0,93
CDET	0,97	0,99	0,002	0,02	0,35	0,94	0,92
SOBS2	0,93	0,99	0,002	0,06	0,39	0,92	0,92
SOBS3	0,91	0,99	0,002	0,08	0,43	0,92	0,93
GPRMF	0,9	0,99	0,002	0,09	0,46	0,92	0,95
PSP	0,93	0,99	0,002	0,06	0,41	0,92	0,96
S-360_1	0,96	0,99	0,003	0,03	0,42	0,93	0,90
MLBS	0,84	0,99	0,001	0,15	0,89	0,90	0,96
DPGMM	0,96	0,99	0,003	0,03	0,49	0,92	0,89
PBAS1	0,95	0,99	0,002	0,04	0,48	0,92	0,89
SGMM	0,93	0,99	0,002	0,06	0,54	0,92	0,91
PBAS2	0,95	0,99	0,003	0,04	0,48	0,92	0,89
KDE1	0,89	0,99	0,002	0,10	0,54	0,90	0,92
BB	0,73	0,99	0,001	0,26	0,90	0,82	0,96
CDPS	0,94	0,99	0,003	0,05	0,62	0,92	0,89
HIST	0,87	0,99	0,002	0,12	0,66	0,90	0,92
CWD	0,89	0,99	0,002	0,10	0,66	0,90	0,91
KNN	0,79	0,99	0,002	0,20	1,28	0,84	0,92
GMM1	0,58	0,99	0,001	0,41	1,93	0,71	0,95
MAHAL	0,88	0,99	0,003	0,11	0,72	0,89	0,90
CHEB1	0,82	0,99	0,003	0,17	0,83	0,86	0,91
RMOG	0,70	0,99	0,001	0,29	1,59	0,78	0,91
LSS	0,97	0,98	0,013	0,02	1,33	0,84	0,75
GMM2	0,80	0,99	0,002	0,19	1,32	0,83	0,89
ED	0,83	0,99	0,004	0,16	1,02	0,87	0,91
GMM3	0,66	0,99	0,002	0,33	1,53	0,75	0,91
SGMM	0,86	0,99	0,005	0,13	1,24	0,85	0,85
DIFF*	**0,82**	**0,99**	**0,004**	**0,17**	**0,94**	**0,84**	**0,87**
UBA	0,90	0,99	0,008	0,09	1,01	0,81	0,74
PROST	0,84	0,99	0,006	0,15	1,15	0,82	0,81
GMM4	0,81	0,99	0,005	0,18	1,53	0,82	0,84
TUBI	0,89	0,98	0,015	0,10	2,08	0,76	0,67
KDE2	0,74	0,99	0,004	0,25	1,80	0,73	0,79
KDE3	0,75	0,99	0,00	0,24	1,91	0,75	0,78
QCHMD	0,70	0,99	0,007	0,29	2,21	0,66	0,70

Table 2. Baseline category. DIFF* - proposed method.

	Ranks among 38 methods							
	RE	SP	FPR	FNR	PWC	F	PR	Overal
DIFF	26	29	29	26	22	24	28	30/38

Table 3. Baseline category. Rank for each metric for proposed method presented.

Results for «Thermal» category is shown in Table 4, 5, 6.

DIFF	TP	FP	FN	TN
corridor	10667192	7675519	1672965	352311506
dining	16264143	4775408	3200154	202408859
lakeSide	5035690	26973588	2937391	381184826
library	58508839	3889517	3452426	255590998
park	384658	48641	330479	34446499
thermal	*90860522*	*43362673*	*11593415*	*1225942688*

Table 4. Thermal category. Results for each video in this category.

Method	RE	SP	FPR	FNR	PWC	F	PR
DIFF	0,76	0,98	0,025	0,23	3,31	0,67	0,67

Table 5. Thermal category.

Ranks among 38 methods							
RE	SP	FPR	FNR	PWC	F	PR	Overall

DIFF	7	37	37	7	24	24	37	32/38

Table 6. Thermal category. Rank for each metric for proposed method presented.

Results for «Bad Weather» category is shown in Table 7, 8, 9.

DIFF	TP	FP	FN	TN
blizzard	8105421	114550	4151098	1038823675
skating	11950348	2149566	2823328	281628841
snowFall	5100041	931585	2656794	975209889
wetSnow	3439753	694655	2575110	460144956
weather	*28595563*	*3890356*	*12206330*	*2755807361*

Table 7. Bad Weather category. Results for each video in this category.

Methods	RE	SP	FPR	FNR	PWC	F	PR
DIFF	0,68	0,99	0,002	0,32	0,78	0,76	0,88

Table 8. Bad Weather category.

	Ranks among 22 methods							
	RE	**SP**	**FPR**	**FNR**	**PWC**	**F**	**PR**	**Overall**
DIFF	12	16	16	12	14	9	11	15/22

Table 9. Bad Weather category. Rank for each metric for proposed method presented.

Results for «Low Frame-Rate» category is shown in Table 10, 11, 12.

DIFF	TP	FP	FN	TN
port	19425	83230	26366	153835893
tram	290806	96304	64765	12357342
tunnel	1283430	135444	3702953	176739284
turn	1355782	259399	450049	22203801
low fr. r.	*2949443*	*574377*	*4244133*	*365136320*

Table 10. Low Frame-Rate category. Results for each video in this category.

Methods	RE	SP	FPR	FNR	PWC	F	PR
DIFF	0,56	0,99	0,005	0,43	1,59	0,55	0,67

Table 11. Low Frame-Rate category.

	Ranks among 22 methods							
	RE	**SP**	**FPR**	**FNR**	**PWC**	**F**	**PR**	**Overall**
DIFF	18	10	10	18	13	8	8	13/22

Table 12. Low Frame-Rate category. Rank for each metric for proposed method presented.

From conducted experiments we conclude that the proposed approach can be used for background modelling, performs better than several well-known methods or is comparative to them in case of different shooting conditions.

CONCLUSION

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APPENDIX

C++ - LIKE SOURCE CODE FOR OUR COMPLEX LBP DIFFISUION FILTERING

Pseudo-code of Diffusion filtering and processing that is used in Diffusion Background Model.

```
class Diffusion
{
public:
unsigned char**  Image1;
unsigned char**  Image2;
int**  OutImage1;
int**  OutImage2;
int**  summs;
__int64**  LBP;
int ExpTableInt[65];
int lbpthr, ithr;
int BlockSize;
int step;
int WSize;
int imW, imH;
double E;

Diffusion(int W, int H)
{
// a small parameter comparable to the
smallest // distances between two feature
vectors v(p) // and v(q)
 E = 10;
// LBP threshold
 lbpthr = 10;
// Intensity threshold
 ithr = 50;
// Half of the sliding window (neighbourhood)
 BlockSize = 5;
 WSize = BlockSize; step = 1;
// Pre-calculating table values for exponent
 for (int i = 0; i < 65; i++)
  ExpTableInt[i] = (int)(exp(-i / E) * 1024);
  imW = W; imH = H;
 Image1 = new unsigned char*[H];
 Image2 = new unsigned char*[H];
 LBP = new __int64*[H];
 LBP[0] = new __int64[W*H];
 summs = new int*[H];
 summs[0] = new int[H*W];
 OutImage1 = new int*[H];
 OutImage1[0] = new int[H*W];
 OutImage2 = new int*[H];
 OutImage2[0] = new int[H*W];
 for (int i = 1; i < H; i++)
 {
  LBP[i] = &LBP[0][i*W];
  OutImage1[i] = &OutImage1[0][i*imW];
  OutImage2[i] = &OutImage2[0][i*imW];
  summs[i] = &summs[0][i*imW];
 }
}

~Diffusion()
{
 delete[] Image1; delete[] Image2;
 delete[] LBP[0]; delete[] LBP;
 delete[] summs[0]; delete[] summs;
 delete[] OutImage1[0]; delete[] OutImage1;
 delete[] OutImage2[0]; delete[] OutImage2;
}

//diffusion filtering of image1 by itself
void Process(unsigned char* image1)
{
 for (int i = 0; i < imH; i++)
  Image1[i] = &image1[i*imW];
  BuildLBPMap();
  Filter();
}

//diffusion projection of image2 on the form of
//image1
void Project(unsigned char* image1, unsigned
             char* image2)
{
 for (int i = 0; i < imH; i++)
 {
  Image1[i] = &image1[i*imW];
  Image2[i] = &image2[i*imW];
 }
  BuildLBPMap();
  MorphProject();
}

// LBP pre-calculation with lbpthr threshold
void BuildLBPMap()
{
```

```
 if (WSize >= 4)
 WSize = 3; WSize *= step;
 for (int x = WSize; x < imW - WSize; x++)
 for (int y = WSize; y < imH - WSize; y++)
 {
  int ind = 0;
  __int64 Res = 0;
  int Pix = Image1[y][x];
  for (int x2 = -WSize; x2 < WSize; x2 +=
step)
  for (int y2 = -WSize; y2 < WSize; y2 +=
step)
  {
   if (Pix - Image1[y + y2][x + x2] > lbpthr)
   Res += ((__int64)2) << ind;
   ind++;
  }
  LBP[y][x] = Res;
 }
}

// bit counting
unsigned int POPCNT(__int64 Arg)
{ unsigned int* t = (unsigned int*)&Arg;
  return (__popcnt(t[0]) + __popcnt(t[1]));}

// heat kernel calculation
int CompareHammingint(__int64 A, __int64 B)
{ return ExpTableInt[POPCNT(A^B)]; }

void Filter(){
memset(&summs[0][0], 0, imW*imH * 4);
memset(&OutImage1[0][0], 0, imW*imH * 4);
int Wd2 = BlockSize; int x, y;
for (int y = 0; y < imH - Wd2; y++){
for (int x = Wd2; x < imW - Wd2; x++){
for (int y2 = 0; y2 < BlockSize; y2 += step)
for (int x2 = -BlockSize; x2 < BlockSize; x2
+= step){
int t = CompareHammingint(LBP[y][x], LBP[y +
y2][x + x2]);
if (abs(Image1[y][x] - Image1[y + y2][x + x2])
> ithr) t = 0;
summs[y][x] += t;
summs[y + y2][x + x2] += t;
OutImage1[y][x] += t * Image1[y + y2][x + x2];
OutImage1[y + y2][x + x2] += t * Image1[y][x];
} OutImage1[y][x] /= (summs[y][x]);
}}}

void MorphProject(){
memset(&summs[0][0], 0, imW*imH * 4);
memset(&OutImage1[0][0], 0, imW*imH * 4);
memset(&OutImage2[0][0], 0, imW*imH * 4);
int Wd2 = BlockSize; int x,y;
for (int y = 0; y < imH - Wd2; y++){
for (int x = Wd2; x < imW - Wd2; x++){
for (int y2 = 0; y2 < BlockSize; y2 += step)
for (int x2 = -BlockSize; x2 < BlockSize; x2
+= step){
int t = CompareHammingint(LBP[y][x], LBP[y +
y2][x + x2]);
if (abs(Image1[y][x] - Image1[y + y2][x + x2])
> ithr) t = 0;
summs[y][x] += t;
summs[y + y2][x + x2] += t;
OutImage2[y][x] += t * Image2[y + y2][x + x2];
OutImage2[y + y2][x + x2] += t * Image2[y][x];
OutImage1[y][x] += t * Image1[y + y2][x + x2];
OutImage1[y + y2][x + x2] += t * Image1[y][x];
}
OutImage1[y][x] /= (summs[y][x]);
OutImage2[y][x] /= (summs[y][x]);
}}}};
```