Near-duplicate Fragments in Simultaneously Captured Videos
A Study on Real-time Detection using CBVIR Approach

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Keywords: Visual Surveillance, CBVIR, Real Time, Keypoint Matching, Keypoint Descriptors, MSER, SIFT.

Abstract: CBVIR approach to video-based surveillance is discussed. The objective is to detect in real time near-duplicates (e.g. similarly-looking objects) simultaneously appearing in concurrently captured/played videos. A novel method of keypoint matching is proposed, based on keypoint descriptions additionally incorporating visual and geometric contexts. Near-duplicate fragments can be identified by keypoint matching only. The analysis of geometric constraints (a bottleneck of typical CBVIR methods for sub-image retrieval) is not required. When the proposed method is fully implemented, high-speed and good performances can be achieved, as preliminarily shown in *proof-of-concept* experiments. The method is affine-invariant and employs typical keypoint detectors and descriptors (MSER and SIFT) as the low-level mechanisms.

1 INTRODUCTION

Content-based visual information retrieval (*CVBIR*) is an important area of machine vision. Typical applications, however, seem to focus on offline tasks, e.g. image retrieval from a large visual database. One of the most challenging problems is the retrieval of near-duplicates, i.e. the returned database images and the query should share some visually similar fragments (similar objects) while the remaining contents of images can be different (e.g. Zhao and Ngo, 2009, Chum et al., 2009).

Real-time retrieval in video sequences of contents similar to given images is a typical problem of automatic visual surveillance. It can be noted that such a task is conceptually similar to *CVBIR* applications. In visual surveillance, each frame is actually a query that should be quickly processed and matched against a very small "database" (of images depicting the object of interest). Thus, the underlying mechanisms are almost the same even though computational requirements and timing constraints are rather different. Some works on *CBVIR* actually use retrieval in videos as case studies (e.g. Sivic and Zisserman, 2003 or Zhao et al., 2007). In fact, the original work by Sivic and Zisserman, 2003, proposed the concept of *visual words* for video search, although the real-time object retrieval was not possible because of computational costs. Nevertheless, examples of real-time surveillance systems which apply *CBVIR* algorithms are known (e.g. Sluzek and Paradowski, 2010).

The goal of this paper is to further explore this approach. Generally, our objective is to evaluate feasibility of *CBVIR*-based systems which continuously acquire video signals from several sources and detect in real time cases of near-duplicate fragments (objects) **simultaneously appearing in at least two of these videos**. No pre-existing knowledge about the contents and topics of the videos is assumed. Therefore, the employed algorithms and mechanisms should allow an immediate switch from one domain to another without retraining.

From the perspective of *CBVIR*, this is a system with a small, dynamically modified database (a number of frames simultaneously captured from several cameras) where each element of the database is also used as a query.

In Section 2, the problem's challenges are discussed. Section 3 presents recent algorithmic tools to be applied. The core idea is to incorporate properties of neighbourhoods in the feature descriptors (a generalization of *feature bundling*, e.g. Romberg et al., 2012) so that semi-local visual similarities can be easily established.

Section 4 presents a limited-scale proof-of-concept verification of these tools and estimates the

Sluzek, A.
Near-duplicate Fragments in Simultaneously Captured Videos - A Study on Real-time Detection using CBVIR Approach.
DOI: 10.5220/0005971902320237
In *Proceedings of the 13th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2016) - Volume 2*, pages 232-237
ISBN: 978-989-758-198-4

overall performances of a complete system. The concluding remarks are given in Section 5.

2 BACKGROUND WORKS

2.1 Keypoint Detection and Description

In order to build a surveillance system based on the concept of sub-image retrieval, keypoint detection, description and matching should be applied as the low-level tools. Therefore, real-time performances of keypoint detection and description are core requirements to deploy such a system.

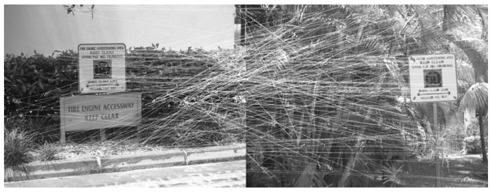
Numerous keypoint detectors exist (e.g. Tuytelaars and Mikolajczyk, 2008) but affine-invariant ones are recommended because of their robustness and repeatability under perspective distortions. Therefore, our choice is *MSER* detector (Matas et al., 2002) which is apparently the only affine-invariant keypoint detector with hardware implementations reported (e.g., Kristensen and MacLean, 2007, and Salahat et al., 2014). In the subsequent sections of this paper we can assume, therefore, that real-time *MSER* detection is achievable.

Numerous hardware-based implementations of keypoint descriptors have been reported as well. They are usually discussed in conjunction with keypoint detection (e.g. Cornelis and Van Gool, 2008) but in Suzuki, 2012, the keypoint description component can be run independently.

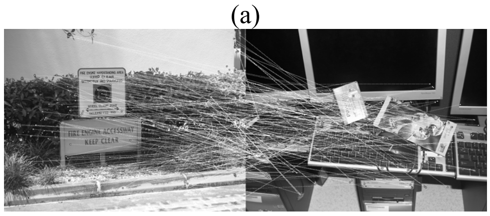
Altogether, we can conclude real-time *MSER* detection and the corresponding *SIFT* description are available. Even if additional modules are needed to convert *MSER* regions into the best-fit ellipses (and the subsequent circular normalization) these are relatively straightforward operations for which hardware solutions have been reported as well, e.g. Paschalakis et al., 2003, Salahat et al., 2014, etc.

2.2 Keypoint Matching

Keypoint matching can be done by using either descriptor vectors or descriptors quantized into *visual words*. However, individual keypoint matches are virtually useless for sub-image matching (even if large vocabularies or the most credible matching schemes are used). For example, our unpublished study shows that in a collection of 135,460 pairs of random-content images, where 511 pairs contain the same object(s), *precision* of keypoint matching is around 0.1% (depending on the matching scheme, the size of visual vocabulary, etc.). Numerical results are given in the first row of Table 1, and two illustrative examples (where no significant differences between a relevant pair and an irrelevant pair of images can be noticed) are shown in Fig. 1.



(a)



(b)

Figure 1: Exemplary matches between affine-invariant keypoints (using SIFT descriptors): (a) for a pair of images sharing a similar object and (b) for a pair of image without similar objects.

Because of that, most reported techniques for sub-image retrieval are based on the *hypothesize-and-verify* paradigm. Various approaches can used to verify validity of preliminarily matched keypoints, e.g. RANSAC and its derivatives (Sivic and Zisserman, 2003), Hough transform, hashing (e.g. Chum et al., 2009), entropy (e.g. Zhao and Ngo, 2009), etc. Eventually, similarly looking fragments are identified as groups of matching keypoints for which a consistent mapping between both images has been found. This approach (in spite of major improvements in the verification methods) is not fully scalable to real-time applications because of the complexity issues.

Additionally, some of typical assumptions of *CBVIR* have to be reformulated in the context of real-time detection of similar fragments from simultaneously acquired videos:

a) High *precision* of retrieval is more critical than *recall*. Errors of low *recall* can be corrected by repeatable detection in subsequent frames. If *precision* is too low, the errors cannot be corrected.
b) The costs of assigning words to the keypoints are comparable (or higher) to the costs of descriptor matching (unless the words are assigned hierarchically, e.g. Nister and Stewenius, 2006). Thus, both approaches can be alternatively used.
c) Image pre-retrieval is usually not needed because the numbers of image pairs to be matched are

rather small (e.g. 15 image pairs for 6 cameras, 45 image pairs for 10 cameras, etc.).

d) Computational costs of consistency verification are the bottleneck of the retrieval process. Even though systems performing such a verification in real time have been reported (e.g. Paradowski, 2010) the approach is generally not scalable to larger numbers of video-cameras.

Thus, in this paper we present an alternative approach. The main novelty consists in the modified keypoint description. Original descriptors are enriched by the neighbourhood data so that *individual keypoint matches* become credible indicators that the compared images contain similar fragments.

3 DETECTION OF NEAR-DUPLICATE FRAGMENTS

The significance of keypoint context has been recognized and exploited from the early days of *CBVIR*. For example, Schmid and Mohr, 1997, verified credibility of keypoint matching by considering additional matches within the corresponding neighbourhoods. Other examples include geometric min-hashing (Chum et al., 2009), feature bundling (e.g. Romberg et al., 2012), etc.

Similarly to these works, we define the keypoint context as a collection of other keypoints within a reasonably sized neighbourhood. Formally, the *context* of K keypoint (represented by E ellipse) is defined as a set of at most N closest keypoints $\{K_1,\dots, K_N\}$ with $\{E_1,\dots, E_N\}$ ellipses, which satisfy:

1. The Mahanalobis distance $D_M(K, K_i) < 1.5$ and $D_M(K, K_i) > 0.7$ (where the unit distance is defined by the ellipse E), i.e. keypoints which are too far or too close to K are excluded.
2. E_i ellipses have sizes comparable to E, e.g. $0.5area(E) \le area(E_i) \le 2area(E)$.

The proposed value of N is 12 (which compromises complexity and performances).

3.1 Description of Keypoint Context

Assuming that an individual *MSER* keypoint K is represented by a visual word (e.g. *SIFT* word) $SW(K)$, the keypoint neighbourhood (context) can be defined by a *bag of words BoW*

$$BoW(K) = \{SW(K_1),\dots,SW(K_N)\} \tag{1}$$

Then, two keypoints K and L would be matched if they are assigned the same word (i.e. $SW(K)$ = $SW(L)$) and their *BoW's* sufficiently overlap, i.e.

$$\|BoW(K) \cap BoW(L)\| \ge M \tag{2}$$

Performances of such an approach (which was used, for example, in Schmid and Mohr, 1997, and Romberg et al., 2012) are rather limited.

The experiment reported in Table 1 indicates that even the optimum values of M have unacceptably low performances (*precision* in particular). Again, the same dataset of 135,460 image pairs is used.

Table 1: Keypoint matching and image pair retrieval by using MSER keypoints and their contexts. $M = 0$ means that the keypoint context is not used at all.

M	Precision of keypoint matching	Retrieved image pairs (correct)	Comment
0	0.11%	135,460 (511)	Poor *precision*. (ALL image pairs retrieved).
2	0.36%	131,683 (499)	Almost the same as above.
6	**16.55%**	**2285 (381)**	**Optimum (still not satisfactory)**
11	20.19%	257 (89)	Too few correct image pairs retrieved.

3.2 Extended Description of Keypoint Context

The proposed improvements in keypoint context description combine the ideas presented in Sluzek, 2012 and 2014. First, the *SIFT* descriptors of neighbouring keypoints $\{K_1,\dots, K_i,\dots K_N\}$ (and, subsequently, their visual words) are computed over E_i ellipses of these keypoints using $(\overrightarrow{K_i, K})$ vectors as the reference orientations (as illustrated in Fig. 2) instead of the dominant orientations established by the *SIFT* algorithm. Thus, we use symbols $SIFT_K(K_i)$ for so calculated *SIFT*s, and $SW_K(K_i)$ for the corresponding words.

In this way, the bag of words $\{SW_K(K_1),\dots,SW_K(K_N)\}$ at least partially reflects geometry of the keypoint neighbourhoods.

Then, more specific geometric relations between a keypoint and its context are as follows (see also Fig. 3): Given ellipses around the K keypoint and a K_i keypoint of its context, four triangles $\Delta(A,B,C)$, $\Delta(A,B,K_i)$, $\Delta(A_i,B_i,C_i)$ and $\Delta(A_i,B_i,K)$ are unambiguously defined by shapes and relative locations of both ellipses.

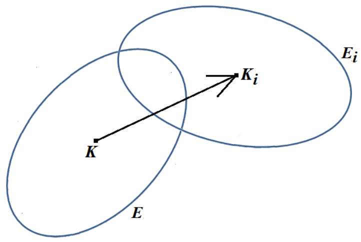


Figure 2: A configuration of a main keypoint K and its neighbour K_i for computing *SIFT* descriptor of the latter.

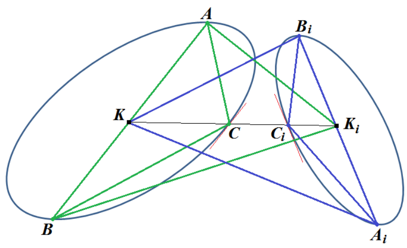


Figure 3: A configuration of two ellipses with four triangles defined by shapes and locations of the ellipses.

When two ellipses are jointly transformed by an affine mapping, the geometry of triangles changes correspondingly. Since all triangles are equivalent under affine transformations, we chose pairs of triangles to identify pairs of keypoints which are covariantly transformed.

The simplest affine-invariant moment expression (see Flusser and Suk, 1993)

$$Inv = \frac{M_{20}M_{02} - 4M_{11}^2}{M_{00}^4} \qquad (3)$$

is applied to three additive unions of triangle pairs to form a 3D invariant descriptor *MPT* (*Moments over Pairs of Triangles*) representing geometry of the keypoint K and its neighbour K_i :

$$MPT(K,K_1) = [Inv(PT_1), Inv(PT_2), Inv(PT_3)], \quad (4)$$

where (a) $PT_1 = \Delta(A,B,C) \cup \Delta(A,B,K_1)$;

(b) $PT_2 = \Delta(A_1,B_1,C_1) \cup \Delta(A_1,B_1,K)$ and

(c) $PT_3 = \Delta(A,B,K_1) \cup \Delta(A_1,B_1,K)$.

MPT descriptors can also be quantized into a finite number of *MW* words. Eventually, the keypoint neighbourhood is described by a *bag of pairs of words BoPW*, where each pair consists of a $SW_K(K_i)$ word and a $MW(K,K_1)$ word:

$$BoPW(K) = \{[SW_K(K_1), MW(K,K_1)], \ldots \\ \ldots, [SW_K(K_N), MW(K,K_N)]\}. \qquad (5)$$

With the proposed extended descriptions, keypoints can be matched straightforwardly. Two keypoints K and L are considered a match if:

(1) They share the same *SIFT* words (i.e. $SW(K) = SW(L)$), and
(2) Their *bags of pairs of words BoPW* sufficiently overlap, i.e.

$$\|BoPW(K) \cap BoPW(L)\| \geq M \qquad (6)$$

3.3 Performance Evaluation

Preliminary evaluation has been performed on the same dataset of 135,460 pairs of random-content images, where 511 pairs contain identically looking object(s). *MSER* keypoints are represented by *SIFT* descriptors quantized into 2048 words. The number looks small compared to typical *CBVIR* systems (e.g. Stewenius et al., 2012) but the actual vocabulary size is $2048^2 = 4{,}194{,}304$ because the words are used in conjunction with the words of neighbours (Eqs 5 and 6) so that sufficiently good *precision* can be achieved.

The size of *MPT* vocabulary is also small, i.e. $\mathbf{9^3}$ (some alternatives are given in Table 2 as well).

Both *SIFT* and *MPT* vocabularies are built using the statistical approach (instead of standard *k-means* technique) so that quantization of descriptors into words can be done instantaneously.

Table 2: Retrieval of relevant (sharing the same objects) pairs of images using extended description of keypoint context. The size of *SIFT* vocabulary is constant (2048).

M	Size of *MPT* voc.	*Precision* and *recall* of image retrieval.	Avg. no of matches found in relevant (irrelevant) pairs of images.
3	729 (9^3)	*p*=20.5%; *r*=70.1%	2.417 (0.036)
4	27 (3^3)	*p*=12.4%; *r*=76.3%	3.337 (0.104)
4	**729 (9^3)**	***p*=76.1%; *r*=57.1%**	**1.683 (0.003)**
5	125 (5^3)	*p*=24.7%; *r*=61.5%	1.593 (0.014)
6	27 (3^3)	*p*=23.5%; *r*=60.3%	1.675 (0.018)

In general, very few keypoint correspondences are found by the proposed method (see the last column of Table 2). Thus, a pair of images is matched (i.e. presumably containing the same object(s)) if at least one correspondence between keypoints from both images is found.

Figure 4: Exemplary ambiguities in the interpretation of keypoint matching.

The variant highlighted in Table 2 provides the best *precision*, while *recall* is only moderately lower. As mentioned in Section 2.2, *precision* is more important in matching simultaneously captured videos. Therefore, we decided to use the highlighted settings in the preliminary experiments on the actual videos (see Section 4).

Finally, some ambiguities in the interpretation of keypoint matching should be mentioned. Examples in Fig. 4 show matches which are semantically incorrect (keypoints are found in different objects) but correct from a purely visual perspective (the indicated fragments are near-duplicate).

4 PRELIMINARY EXPERIMENTS

4.1 Setup

Proof-of-concept experiments have been conducted using a small collection of indoor-captured videos of VGA resolution (exemplary frame sequences are shown in Fig. 5). The system is implemented in two separate Matlab modules. The first module (which could be eventually replaced by the hardware-based solutions, see Section 2.1) detects MSER keypoints and describes them by the extended descriptors according to Section 3.2.

In the second module, frames from two videos (represented by descriptions built in the 1st module) are matched at 5 frames/sec rate. We believe that much higher frame rates can be achieved after converting the module to C++.

4.2 Exemplary Results

Figs 6 and 7 show exemplary results (for the sequences from Fig. 5). The examples are selected to illustrate some limitations of the method.

In Fig. 6, one pair of frames is undetected, and one pair contains two incorrectly matched keypoints. Pairs of frames in Fig. 7 are not supposed to be matched but, nevertheless, one keypoint correspondence is actually found.

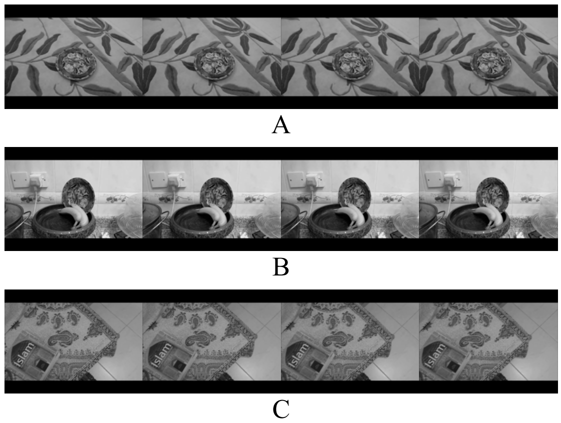


Figure 5: Exemplary sequences of frames with complex contents. Sequences (A) and (B) contain the same object.

Incorrect keypoint matches appear rather incidentally (see statistics in Table 2) and randomly, so that we use a simple majority voting (the results from the most recent 4 frames) to decide whether the videos contain near-identical objects. In case of a draw, the decision is postponed until the next frames are processed. Thus, in both examples shown in the figures, the final decisions are correct.

Figure 6: Matching results for sequences (A) and (B) from Fig. 5. Note an undetected pair of frames and two incorrect keypoint correspondences.

Finally, it should be noted that a single match actually indicates several matches between a few keypoints from the corresponding contexts. If necessary, those keypoints can be identified and used to estimate more accurately sizes and shapes of the detected near-duplicate fragments.

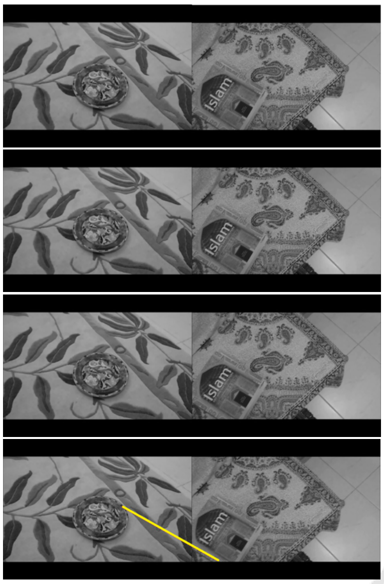


Figure 7: Results for sequences (A) and (C) from Fig. 5. One incorrect keypoint correspondence can be seen.

5 CONCLUSIONS

The paper demonstrates that *CBVIR* techniques are a feasible option for a multi-camera video surveillance. It is shown that near-duplicates simultaneously seen by several cameras can be fairly reliably detected. Limited performances of the approach can be rectified by combining results from a number of subsequent frames. No assumptions about the image backgrounds and the type/number of objects are required.

A novel affine-invariant description of keypoints (incorporating the keypoint contexts) is a core element of the method. By using such descriptions, similar image fragments can be identified by individual keypoint correspondences, i.e. verification of configuration constraints (required in typical retrieval algorithms) is not needed.

REFERENCES

Zhao, W-L., Ngo, C-W., 2009. Scale-rotation invariant pattern entropy for keypoint-based near-duplicate detection. *IEEE Trans. Image Proc*., 18(2): 412-423.

Chum, O., Perdoch, M., Matas, J., 2009. Geometric min-hashing: Finding a (thick) needle in a haystack. Proc. IEEE Conf. CVPR'09: 17–24.

Sivic, J., Zisserman. A., 2003. Video Google: A text retrieval approach to object matching in videos. *Proc.* 9th *IEEE Int. Conf. ICCV'*03: 1470-1477.

Zhao, W.-L., Ngo, C.-W., Tan, H.-K. and Wu, X., 2007. Near-duplicate keyframe identification with interest point matching and pattern learning. *IEEE Trans. Multimedia*, 9(5): 1037–1048.

Paradowski, M., Sluzek, A., 2010. Real-time retrieval of near- duplicate fragments in images and video-clips. *Proc. ACIVS* 2010 (*LNCS* 6474): 18-29.

Romberg, S., August, M., Ries, Ch.X. and Lienhart, R., 2012. Robust Feature Bundling. *Proc. PCM* 2012 (*LNCS* 7674): 45-56.

Tuytelaars, T., Mikolajczyk, K., 2008. *Local inavariant feature detectors: A survey*, Now Publishers Inc.

Matas, J., Chum, O., Urban, M. and Pajdla, T., 2002. Robust wide baseline stereo from maximally stable extremal regions, *Proc. BMVC*'02: 384–393.

Kristensen, F., MacLean, W.J., 2007. Real-time extraction of maximally stable extremal regions on an FPGA, *Proc. IEEE Symp. ISCAS*'07: 165-168.

Salahat, E., Saleh, H., Sluzek, A., Al-Qutayri, M., Mohammed, B., and Ismail, M., 2016. Architecture and method for real-time parallel detection and extraction of maximally stable extremal regions (MSERs), *U.S. Patent* 9,311,555.

Cornelis, N., Van Gool, L., 2008. Fast scale invariant feature detection and matching on programmable graphics hardware, *Proc. IEEE Conf. CVPR*'08 Workshop: 1-8, 2008.

Sluzek, A., 2012. Large vocabularies for keypoint-based representation and matching of image patches, *Proc. ECCV'*12 *W&T* (*LNCS* 7583): 229–238.

Suzuki, T., 2012. SIFT-based low complexity keypoint extraction and its real-time hardware implementation for full-HD video, *Proc. APSIPA*'12 *Annual Summit and Conf*.: 1-6.

Paschalakis, S., Lee, P. and Bober, M., 2003. An FPGA system for the high speed extraction, normalization and classification of moment descriptors, *Proc.* 13 *Int. Conf. FPL*'03 (*LNCS* 2778): 543-552.

Nister, D., Stewenius, H., 2006. Scalable recognition with a vocabulary tree, *Proc. IEEE Conf. CVPR*'06: 2161-2168.

Jegou, H., Douze, M. and Schmid, C., 2010. Improving bag-of-features for large scale image search, *Int. J. Comp. Vision* 87(3): 316–336.

Schmid, C., Mohr, R., 1997. Local grayvalue invariants for image retrieval. *IEEE Trans PAMI* 19(5): 530–534.

Sluzek, A., 2014. Extended keypoint description and the corresponding improvements in image retrieval, *Proc. ACCV* 2014 *Workshops,* (*LNCS* 9008): 698-709.

Flusser, J., Suk, T., 1993. Pattern recognition by affine moment invariants, *Pattern Recognition* 26: 167–174.

Stewenius, H., Gunderson, S., Pilet, J., 2012. Size matters: Exhaustive geometric verification for image retrieval. *Proc. ECCV'*12 (*LNCS* 7573): 674-687.