Efficient Self-similarity Range Wide-joins Fostering Near-duplicate Image Detection in Emergency Scenarios

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Abstract: Crowdsourcing information is being increasingly employed to improve and support decision making in emergency situations. However, the gathered records quickly become too similar among themselves and handling several similar reports does not add valuable knowledge to assist the helping personnel at the control center in their decision making tasks. The usual approaches to detect and handle the so-called near-duplicate data rely on costly twofold processing. Aimed at reducing the cost and also improving the ability of duplication detection, we developed a framework model based on the similarity wide-join database operator. We extended the wide-join definition empowering it to surpass its restrictions and accomplish the near-duplicate task too. In this paper, we also provide an efficient algorithm based on pivots that speeds up the entire process, which enables retrieving the top similar elements in a single-pass processing. Experiments using real datasets show that our framework is up to three orders of magnitude faster than the competing techniques in the literature, whereas also improving the quality of the result in about 35 percent.

1 INTRODUCTION

Emergency situations can threaten life, environment and properties. Thus, a great effort are being made to develop systems aimed at reducing injuries and financial losses in crises situations. Existing solutions employ ultraviolet, infrared sensors and surveillance cameras (Chino et al., 2015). The problem of using sensors is that they need to be installed near to the prospected emergency places, and forecasting all the possible crisis situations in a particular region is not feasible.

On the other hand, surveillance cameras can provide visual information of wider spaces. When associated the increasing popularity of smartphones with good quality cameras and other mobile devices, they may lead to better solutions to map crisis scenarios and allow speeding up planning emergency actions to reduce losses. Seizing the opportunity to take such information into accont, the Rescuer[1] Project is developing an emergency-response system to assist Crisis Control Committees during a crisis situation. It provides tools that allow witnesses, victims and the rescue staff to gather emergency information based on images and videos sent from the incident place using a mobile crowdsourcing framework.

Crowdsourcing data can provide a large amount of information about the emergency scenario, but it often leads to a large amount of records very similar among themselves too. For instance, let us consider the occurrence of an event such as a building on fire or a serious incident in an industrial plant. As the eyewitnesses register the event with their smartphones many and repeatedly times, several pictures become copies almost identical to others. In the image retrieval context, the images too similar to each other with only smooth variations imposed by the devices or the capture conditions (resolution, illumination, cropping, rotation, framing) are called *near-duplicates* (Li et al., 2015; Yao et al., 2015).

For instance, Fig. 1 depicts a 9 days-long fire occurred in an industrial plant at Santos, Brazil, in April 2015. As shown in Fig. 1, eyewitnesses e_1, e_2 and e_3 took photos from the same perspective of the burning industrial plant, whereas e_4, e_5 and e_6 took photos from another side of the scenario and the same happened to eyewitness e_7, e_8, e_9 and e_{10}. Too much similar images from the same perspectives (near-duplicates) may not improve the decision making support. In this example, each image subset {img$_1$, img$_2$, img$_3$}, {img$_4$, img$_5$, img$_6$}, {img$_7$, img$_8$, img$_9$} and

[1]Rescuer: Reliable and Smart Crowdsourcing Solution for Emergency and Crisis Management - <http://www.rescuer-project.org>

{img$_{10}$} forms near-duplicates. Thus, it is more useful *to remove* the near-duplicates, fostering more diversified results, which present a holistic vision about the incident, such as using only the subset {img$_1$, img$_6$, img$_8$, img$_{10}$}.

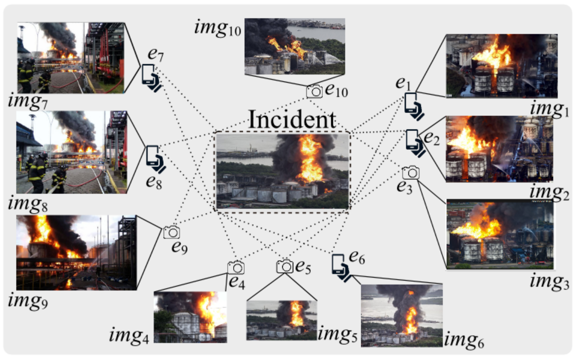


Figure 1: An example of taking photos of an emergency scenario (industrial plant on fire).

On the other hand, sometimes it is interesting to *retrieve* and *return* the near-duplicate elements. In the aforestated example (Fig. 1), law enforcement officers and investigators may be interested on the near-duplicate images. Although the near-duplicate elements may be not useful for non-expert people, those professionals usually see things differently and are trained to recognize small details among the images that can contribute to the investigation.

Near-duplicate image detection has attracted considerable attention in multimedia and database communities (Xiao et al., 2011; Wang et al., 2012; Li et al., 2015; Yao et al., 2015). However, to the best of our knowledge, the near-duplicate detection is yet an open problem, with no consolidated technique able to accomplish such task in terms of both efficiency and efficacy. Most of the approaches to detect near-duplicate images rely on executing a twofold processing, described as follows:

1. *Building*: the first phase aims at retrieving a candidate set of near-duplicate elements. It can use every individual image in the dataset as a similarity query center to retrieve the images most similar to each one (Xiao et al., 2011), or employ clustering-based techniques (Li et al., 2015).

2. *Improvement*: the second phase processes the candidate set and refines it removing false positives. The main differences among the distinct methods are in this phase. Most of them sacrifices the computational efficiency to enhance the result efficacy.

Considering the scenario depicted in Fig. 1, it is reasonable to consider that a crowdsourcing framework can be "flooded" with a large amount of images. In that case, employing a twofold technique may take too much time to generate the first perspective about the incident scene and, when it is achieved, the situation may already be changed.

As a possible solution, recent approaches (Xiao et al., 2011; Carvalho et al., 2015) consider using well-known searching operators from both the database and information retrieval areas, namely *similarity joins* and *wide-joins*, to detect near-duplicate elements. Similarity joins (Silva et al., 2013) obtain pairs of elements similar among themselves, assuming each pair corresponds to the near-duplicate candidates obtained by the building phase. However, those retrieval operators were applied only to detect near-duplicate elements in data represented by strings, as in (Xiao et al., 2011), but they were not explored in other domains such as images. In their turn, wide-joins (Carvalho et al., 2015) are designed to retrieve the overall most similar pairs, leading to an inherent combination of building and improvement phases in their processing. However, wide-joins process two distinct sets, while near-duplicate detection must combine a set with itself.

Although employing the join-based techniques may improve the performance, they require computing the similarity among all possible pairs of image received. As the amount of elements is usually large, the situation becomes similar to the first alternative. Therefore, both alternatives present drawbacks when applied to emergency control systems.

To detect near-duplicate images for emergency scenarios efficiently, this paper introduces a framework based on the similarity range wide-join database operator. We extended the operator definition to enable processing a single relation, thus we enlarged its usability as a unary *self wide-join* operator. Moreover, we devised an optimized algorithm based on pivots to speed up processing similarity wide-join, prioritizing early result generation, as required by emergency-based support systems, with no need of further improvement steps. Experiments performed on two real datasets show that our proposal is at least two orders of magnitude faster than existing techniques, whereas always returning a high-quality answer.

The remainder of this paper is organized as follows: Section 2 describes the main concepts and related work. Section 3 introduces our framework to detect near-duplicate images, the definition and algorithms for the self wide-join. Section 4 presents experimental evaluation of our technique and discusses the main results. Finally, Section 5 summarizes the main achievements and outlines future steps.

2 BACKGROUND

This Section overviews the main concepts and the related work to ours regarding to the image representation (Section 2.1), near-duplicates object detection (Section 2.2) and the evaluation of similarity queries, including the types similarity joins (Section 2.3). Also, the main symbols employed along the paper are summarized in Table 1.

2.1 Feature Extraction and Image Representation

Aiming at enabling retrieval by content and hence the near-duplicate detection, images are compared according to a similarity measure. To evaluate the similarity, images are represented by an n-dimensional array of numerical values, called *feature vector*, that describes their content. The features are numerical measurements of visual properties.

The algorithms responsible for processing images and obtaining their features are known as *feature extractors methods*. For each data domain there are specific features to be considered and, in the case of images, the *off-the-shelf* extractors capture features based on colors (e.g. histograms), texture (e.g. Haralick features) and/or shape (e.g. Zernike Moments) (Sonka et al., 2014).

The evaluation of the similarity measure between two feature vectors is performed by a *metric*. Formally, given a feature vector space $\mathbb{D}$ (the data domain), a distance function $d : \mathbb{D} \times \mathbb{D} \mapsto \mathbb{R}^+$ is called a *metric* on $\mathbb{D}$ if, for all $x, y, z \in \mathbb{D}$, there holds:

- $d(x,y) \geq 0$ (non-negativity)
- $d(x,y) = 0 \Rightarrow x = y$ (identity of indiscernibles)
- $d(x,y) = d(y,x)$ (symmetry)
- $d(x,y) \leq d(x,z) + d(z,y)$ (triangle inequality)

The pair $\langle \mathbb{D}, d \rangle$ is called *metric space* (Searcóid, 2007). The metric space is the mathematical model that enables to perform similarity queries, and hence to detect the near-duplicate elements.

2.2 Near-duplicate Detection

Several techniques for near-duplicate detection rely on the Bag-of-Visual Words (BoVW) model (Li et al., 2015; Yao et al., 2015). That model represents the features as *visual words* and the image representation consists of counting the words to create an histogram. However, BoVW reliability for duplicate detection is small, as it does not capture the spatial relationship existing among the extracted features.

Aimed at surpassing this drawback, studies like (Yao et al., 2015) combined the spatial information with the BoVW local descriptors. However, local descriptors yet generate feature vectors of varying dimensionality, which is troublesome to represent in metric spaces, requiring high-costly metrics.

Other approaches considered to spot near-duplicates are hash functions and the Locality Sensitive Hashing (LSH) (Bangay and Lv, 2012; Wang et al., 2012). Whereas hash functions fail on representing information for similarity retrieval, once small differences in images leads to distinct hash representations, the LSH circumvents this problem by retrieving approximate result sets. In the same line, weighted min-Hash functions improve the image representation, but once they are usually based on bag-of-words, they may present the same drawbacks of the other technique (Chum et al., 2008). Unlike those techniques, we are interested in accurate answers.

Still worth to mention is the "Adaptive Cluster with k-means" technique (ACMe) (Li et al., 2015). It applies clustering algorithms to group near-duplicate images in a twofold process. First it clusters the dataset using the k-means algorithm. Subsequently, the coherences of the obtained clusters are checked to determine the need of recursively processing each cluster. The result is then refined using local descriptors. This is a highly expensive technique that requires for the Improvement phase. Moreover, as the k-means algorithm is sensitive to outliers, our intuition is that better quality result might be achieved replacing it with the k-medoids algorithm. Surpassing the existing drawbacks in algorithms that have an improvement phase, our proposal extends similarity joins to speed up the detection of near duplicates without post-processing the image database.

2.3 Similarity Join

Similarity joins are database operators that combine the tuples of two relations T_1 and T_2 so that each retrieved pair $\langle t_1 \in \mathsf{T}_1, t_2 \in \mathsf{T}_2 \rangle$ satisfies a similarity predicate θ_s. The similarity conditions most employed in similarity joins generate the similarity range join and the k-nearest neighbor join (Silva et al., 2013).

Assume that each relation has an attribute $\mathsf{S}_1 \subseteq \mathsf{T}_1$ and $\mathsf{S}_2 \subseteq \mathsf{T}_2$, both sampled from the same metric space $\langle \mathbb{D}, d \rangle$. Given a maximum similarity threshold ξ, the *similarity range join* retrieves the pairs $\langle t_1, t_2 \rangle$, $t_1 \in \mathsf{T}_1$ and $t_2 \in \mathsf{T}_2$, such that $d(t_1[\mathsf{S}_1], t_2[\mathsf{S}_2]) \leq \xi$. Given an integer value $k \geq 1$, the *k-nearest neighbor join* retrieves $k * |\mathsf{T}_1|$ tuples $\langle t_1, t_2 \rangle$ such that t_2 is one

Table 1: Symbols.

SYMBOL	MEANING
ξ	similarity limiar
$\mathbb{D}$	data domain
d	distance function / metric
$\mathfrak{F}$	feature extractor method
f	feature value
img	an image
k, κ, m, n	integer values
$\mathsf{S}, \mathsf{S}_1, \mathsf{S}_2$	attributes subject to a metric
$\mathsf{T}, \mathsf{T}_1, \mathsf{T}_2$	relations
t, t_1, t_2, t_i, t_j	tuples
$t[\mathsf{S}]$	the value of attribute S in tuple t
v	feature vector

of the k most similar attributes to each t_1 (Carvalho et al., 2015).

A third type of similarity join is often described in the database literature (Silva et al., 2013): the k-distance join. It retrieves the k pairs $\langle t_1, t_2 \rangle$ having the most similar values $t_1[\mathsf{S}_1]$ and $t_2[\mathsf{S}_2]$. This operator is an instance of the similarity *wide-join* (Carvalho et al., 2015). Wide-joins retrieve the most similar pairs in general, sorting the tuple internally, allowing its processing to comply with the relational theory and executed efficiently.

Similarity joins can be used to perform several tasks, including near-duplicate detection. For this last purpose, however, similarity joins have been explored only in string-based data represented as tokens, using metrics such as the Edit or Hamming distance, as in (Xiao et al., 2011). Our proposal considers other domains but string data and employs more general metrics, such as the Minkowski (L_p) family over image domains. Likewise, similarity wide-joins have been restricted used to operate on two distinct relations, loosing optimization opportunities that exists when processing elements lying in the same set.

3 NEAR-DUPLICATE DETECTION

Detecting near-duplicates on multimedia repositories plays an important role in presenting a more useful result, as returning images too much similar not only poses a negative impact on the retrieval time, but generally it also reduces the users' browsing experience. Imposing users to interactively analyze near-duplicates until obtaining the desired result is annoying, and requires a lot of time that would be more wisely employed specially when handling emergency scenarios. Following, we present a novel framework to detect near-duplicates (Section 3.1) and an extension of the similarity wide-join definition, which greatly reduces such drawbacks (Section 3.2). Last but not least, Section 3.3 presents the basic approach to implement our proposed wide-join extension and also devises an optimized version based on pivots to achieve an efficient computation.

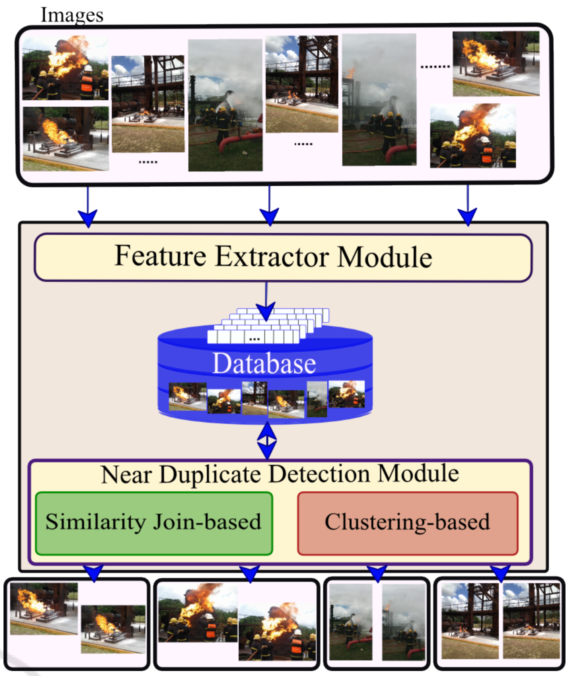


Figure 2: The architecture of the framework for near-duplicate detection.

3.1 The Framework Architecture

The proposed framework is composed of two modules, organized according to Figure 2. The Feature Extractor module processes images such as a content-based image retrieval system, representing them as n-dimensional arrays. Formally, the Feature Extractor module receives an image repository $C = \{img_1, \ldots, img_m\}$ with m images, and extracts the visual features $v_i = \mathfrak{F}(img_i)$ of each image $img_i \in C$. Each v_i is a feature vector $\langle f_1, \ldots, f_n \rangle$, where n is the number of features extracted by the feature extractor method $\mathfrak{F}$. The features depend on the kind of visual aspect considered, e.g., color, shape, texture, etc, as discussed in Section 2.1. Its result is m Feature Vectors stored into the S attribute in relation T such that $\mathsf{T}[\mathsf{S}] = \{v_1, \ldots, v_m\}$, and the corresponding images are stored as another attribute in T.

The second module – Near Duplicate Detection – is the core module of our framework. It can perform either a Similarity Join-based or a Clustering-based near-duplicate detection. Both compare the feature vectors according to a distance function. The detection based on similarity join executes our specialized similarity join operator (described in Section 3.2) on T, employing two user-defined parameters that allows tuning the comparison to follow the user's perception of how pairs of images can be considered as near-duplicates. The Cluster-based detection processes T executing one of the defined clustering techniques: the Adaptive Cluster with k-means (ACMe - Section 2) or our Adaptive Cluster with k-medoids variation (ACMd - Section 4). The framework returns the resulting pairs of images that each algorithm detects as near-duplicates, allowing comparing the considered techniques. Thus, our proposal allows users either removing, preserving or return the near-duplicate according to the interest of users.

3.2 Self Similarity Wide-joins

The similarity joins operators, such as the range join and the k-nearest neighbor join, present shortcomings when employed to query databases. Both of them return result sets whose cardinality is often too high, which leads to many more pairs of elements than users really need or expect. Hence, that large result set usually includes pairs truly similar, as well as pairs holding a low or even questionable degree of similarity. Therefore, to fulfill the near-duplicate task, the result of a similarity join must be further processed in order to exclude the pairs whose the similarity measure is doubtful.

Moreover, the k-nearest neighbor join is also troublesome because it does not assure an equivalent similarity among the k-th nearest pairs from distinct elements. Thus, given two vectors $v_i = t_i[\mathsf{S}]$ and $v_j = t_j[\mathsf{S}]$, the distances ξ_i and ξ_j from v_i to its k-nearest neighbor, let v_{ik}, and from v_j to its k-nearest neighbor, let v_{jk}, are completely uncorrelated. In this way, for any given $k \geq 1$, a pair $\langle v_i, v_{ik} \rangle$ may be a near-duplicate whereas the pair $\langle v_j, v_{jk} \rangle$ may not. Hence, looking at the range ξ variation in the k-neighbors becomes the main focus of our investigation.

Our proposal is that the resulting pairs of a similarity range join must have the similarity between their component elements evaluated and subsequently ranked so that the top-ranked ones correspond to the near-duplicate elements. Such kind of processing can be efficiently achieved by extending the similarity join operator called range wide-join (Section 2).

Wide-joins are intended to compute the similarity join between two relations and retain only the global most similar elements. The near-duplicate detection requires combining a set with itself, but wide-joins do not comply with such processing once the most similar pairs will include combinations of each element with itself, distorting the result.

For this purpose, we employ a tailored version of the wide join operator, namely *self range wide-join*, that atomically performs (i) the similarity evaluation over the *same set or relation* and (ii) the retrieval of the most similar elements in general. Those two operations intrinsically coupled as a single operator enable retrieving the element pairs considered as near-duplicates in a single-pass, avoiding further processing of refinement phase.

Formally, let $\mathbb{D}$ be a data domain, $d : \mathbb{D} \times \mathbb{D} \mapsto \mathbb{R}^+$ be a metric over $\mathbb{D}$, T be a relation, $\mathsf{S} \subseteq \mathsf{T}$ be an attribute subject to d with values sampled from $\mathbb{D}$, ξ be a maximum similarity threshold and κ be an upper bound integer value. The *self similarity range wide-join* is given by Definition 1.

Definition 1 (The Self similarity range wide-join). *The self similarity range wide-join* $\boxed{\Join\!\!\!\!\!\Join_{(\mathsf{S},\xi,\kappa)} \mathsf{T}}$ *is a similarity range join where both left and right input relations* T_1 *and* T_2 *are the same relation* T*, and it returns at most* κ *pairs* $\langle t_1, t_2 \rangle \, | t_1, t_2 \in \mathsf{T}$ *such that* $t_1 \neq t_2$*,* $d(t_1[\mathsf{S}_1], t_2[\mathsf{S}_2]) \leq \xi$ *and the returned pairs are the* κ *closest to each other. The self range wide-join is expressed in relational algebra according to* (1).

$$\Join\!\!\!\!\!\Join_{(\mathsf{S},\xi,\kappa)} \mathsf{T} \equiv$$

$$\pi_{\{\mathsf{T}_1,\mathsf{T}_2\}}\left(\sigma_{(ord \leq \kappa)}\left(\pi_{\{\mathsf{T}_1,\mathsf{T}_2,\mathcal{F}(d(t_1[\mathsf{S}_1],t_2[\mathsf{S}_2]))\rightarrow ord\}}\left(\right.\right.\right.$$

$$\left.\left.\left.\rho_{(\mathsf{S}/\mathsf{S}_1)}(\mathsf{T}/\mathsf{T}_1) \overset{d(t_1[\mathsf{S}_1],t_2[\mathsf{S}_2])\leq\xi}{\bowtie} \rho_{(\mathsf{S}/\mathsf{S}_2)}(\mathsf{T}/\mathsf{T}_2)\right)\right)\right) \tag{1}$$

The self similarity range wide-join is a *unary* operator (it takes one relation) that internally performs a range join, sorts the intermediate result by the dissimilarity among the tuples and returns the top-κ pairs $\langle t_i, t_j \rangle$ of most similar elements in T. In (1), $\mathcal{F}$ is a database aggregate function that receives the distances between the attributes $t_1[\mathsf{S}_1]$ and $t_2[\mathsf{S}_2]$ and projects the ordinal classification of those dissimilarity values into an attribute *ord* that exists only during the operator execution. Further, that transient attribute is used to select the most similar pairs and discarded.

Following (1), the self similarity range join relies on the maximum limiar ξ in order to filter the candidate pairs to compose the answer. This operation is related to the building processing phase, where two images a and b are *possible* near-duplicates *iff* the dissimilarity between them is at most the threshold ξ, that is, $d(a,b) \leq \xi$.

The inner similarity join may be influenced by the data distribution. Each attribute S_1 of the pairs $\langle t_1, t_2 \rangle$

Algorithm 1: NLWJ(T,ξ, κ).

```
1  $Q \leftarrow \varnothing$;
2  for $i \leftarrow 1$ to $|T| - 1$ do
3      for $j \leftarrow i+1$ to $|T|$ do
4          $dist \leftarrow d(t_i[S], t_j[S])$;
5          if $dist \leq \xi$ then
6              if $|Q| \leq \kappa$ then
7                  $Q \leftarrow Q \cup \{\langle\langle t_i, t_j\rangle, dist\rangle\}$;
8              else
9                  Let $q \in Q$ be the high-priority
                   element;
10                 if $dist < d(q[S_1], q[S_2])$ then
11                     $Q \leftarrow Q - \{q\}$;
12                     $Q \leftarrow Q \cup \{\langle\langle t_i, t_j\rangle, dist\rangle\}$;
13 return $Q$;
```

can be combined with varying quantities of values in S_2. Thus, the inner join in (1) retrieves pairs in a large range of distances, but only the smaller distances truly correspond to near-duplicate elements. The greater the distance among S_1 and S_2, the smaller the confidence that the pair is a near-duplicate.

Sorting the self-similarity of the pairs is related to the improvement phase of a near-duplicate process. As it is performed internally by the wide-join, no further processing is required. In addition, that step also solves a frequent issue existing in traditional similarity joins: how to define ξ. Once the self range wide-join sorts the pairs and filters just the closest, the ξ parameter can be overestimated without adversely affecting the quality of the final answer. Moreover, it improves both the query answer quality and the performance of the self similarity range wide-join operator, as it was confirmed by the experiments reported in Section 4.

3.3 Algorithmic Issues

Self similarity range wide-joins can be implemented more efficiently than the sequence expressed in (1), following a strategy based on a nested-loop (Nested-Loop Wide-Join - NLWJ), as depicted in Algorithm 1. Usually, the traditional range wide-join performs n^2 distance computations, where $n = |T|$. However, our self version of the algorithm (steps 2 and 3) requires only half of that amount because, as the join condition is a metric, it meets the symmetry property. Therefore, a first improvement is that it is necessary to compute the distances $d(t_i[S], t_j[S])$ and $d(t_j[S], t_i[S])$ only once, resulting in $n(n-1)/2$ distance calculations.

Following, the κ most similar pairs qualifying as near-duplicates (steps 5-6) are added into a priority queue Q (step 7). The priority parameter is the similarity distance: a greater distance corresponds to a higher priority for removal. After κ pairs were obtained, the current pair $\langle t_i, t_j\rangle$ replaces the higher priority element (q - step 9) whenever it is more similar than q, as tested in step 10. Thus, the second improvement is truncating the sorting operation, as $\mathcal{F}$ in (1) can be incrementally performed by the priority queue, which avoids the cost of sorting the total whole amount of pairs or overflowing memory with too many elements. When the procedure finishes, the priority queue Q already contains the near-duplicate images.

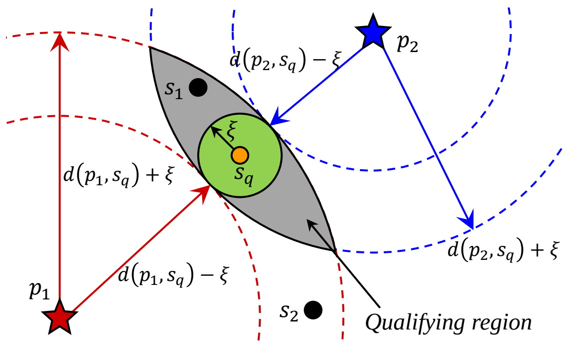


Figure 3: Pivot-based strategy to prune the search space.

Finally, we designed a third improvement to compute self-similarity range wide-joins. The trick here is based on the triangle inequality property of a metric (Section 2), using pivot elements in order to prune the in-list search space and further reduce the number of distance computations.

For an arbitrary and small number $p \ll n$ of pivots chosen among the available element in the database, we first compute the distance between each element $t_i[S]$ to each one of the p pivots. In such manner, each element in the database is filtered by their distances to each pivot. Notice that, until this step, only $p * n$ distance computations were performed.

The next step performs the similarity join. Each element s_q is compared to each elements s_i, and when they are closer than the similarity threshold ξ, the pair is part of the answer. To prune comparisons, it is first verified if s_i is within the qualifying area of s_q regarding to each pivot, assuring that for each pivot p_i the conditions defined in (2) and (3) simultaneously hold.

$$d(p_i, s_i) \geq d(p_i, s_q) - \xi \qquad (2)$$

$$d(p_i, s_i) \leq d(p_i, s_q) + \xi \qquad (3)$$

For instance, element s_2 in Fig. 3 satisfies conditions (2) and (3) with respect to the pivot p_1, i.e., s_2 is within the hyper-ring delimited by the pivot p_1. However, when analyzed in relation to the pivot p_2, s_2 does not satisfy (3), thus it is guaranteed that s_2 is out-side the intersection area among the two hyper-rings. Therefore, the comparison of s_q with s_2 is pruned.

Still considering Fig. 3, notice that the element s_1 holds conditions (2) and (3) with respect to both pivots and should be compared to s_q. In this case, although s_1 is within the qualifying area defined by the two pivots, it is not within the range area of s_q, which can be verified with just one distance computation.

For those elements within the qualifying area, the number of additional distance computations is based on the data distribution and cannot be predicted beforehand. However, the worst and highly improvable situation occurs when the n elements in the database lie within the qualifying area. In this case, it is necessary to perform, for each element s_q, n distance computations, which leads to a total of $np + n(n-1)/2$ calculations. Similar to the nested-loop case, due to the symmetry property of the metric (Section 2), at most a half of all the distance computations are required.

Nevertheless, it is very uncommon and easy to avoid to have all the dataset in the qualifying area. In Fig. 3, notice that making $p = 3$, thus putting a third pivot next to the element s_2, would substantially reduce the qualifying area, restricting it to almost the coverage region of s_q.

The opposite situation occurs when no element qualifies. In that case, there is no distance computation. In average, the number of distance computations can be estimated as the arithmetic mean among the best and worst cases, which leads the required number of distance calculations to be significantly less than $n(n-1+2p)/4$ distance computations, already including the $n*p$ pivot-elements performed calculations.

Similarity wide-join based on pivots (WJ-P) can be implemented in external memory following the block-nested loop approach introduced in Algorithm 2. Similar to Algorithm 1, the WJ-P implementation also relies on a priority queue Q (step 1) in order to achieve the sorting step of similarity wide-joins. In step 2, p pivots are chosen at random. Heuristics on how the pivots should be chosen are out of scope in this paper. Steps 3-6 iterate over the blocks where the tuples are stored. The nested-loop of steps 8 and 12 iterates over the elements inside the blocks. In order to avoid combining a element with itself ensuring a self similarity join, the condition in step 10 increments the start position of the inner loop.

For each pivot picked in step 2, Equations (2) and (3) must hold (step 13). Notice that the distance between the elements and the pivots can be precomputed and stored when reading the elements in the loops of steps 8-12. Step 13 means that the analyzed tuple (t_y)

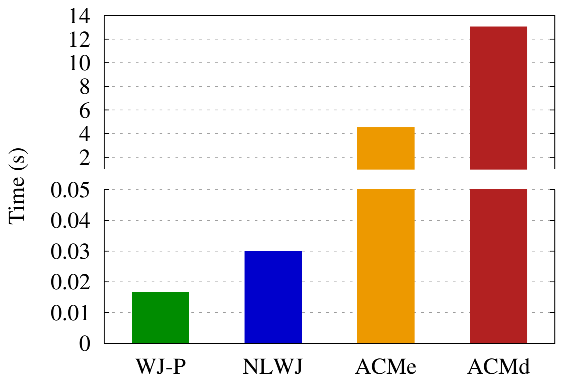
Algorithm 2: WJ-P(T, ξ, κ).

```
1  $Q \leftarrow \varnothing$;
2  Choose $p$ pivots at random in $\mathsf{T}$;
3  for $i \leftarrow 1$ to number of blocks of $\mathsf{T}$ do
4      for $j \leftarrow i+1$ to number of blocks of $\mathsf{T}$ do
5          load block $i$ to memory;
6          load block $j$ to memory;
7          $x \leftarrow 1$;
8          while $x <$ number of elements in block $i$ do
9              $y \leftarrow x$;
10             if $i = j$ then
11                 $y \leftarrow y+1$;
12             while $y <$ number of elements in block $j$ do
13                 if expressions (2) and (3) hold $\forall$ pivot $p$ then
14                     $dist \leftarrow d(t_x[\mathsf{S}], t_y[\mathsf{S}])$;
15                     if $dist \leq \xi$ then
16                         if $|Q| \leq \kappa$ then
17                             $Q \leftarrow Q \cup \{\langle\langle t_x, t_y\rangle, dist\rangle\}$;
18                         else
19                             Let $q \in Q$ be the high-priority element;
20                             if $dist < d(q[\mathsf{S}_1], q[\mathsf{S}_2])$ then
21                                 $Q \leftarrow Q - \{q\}$;
22                                 $Q \leftarrow Q \cup \{\langle\langle t_x, t_y\rangle, dist\rangle\}$;
23 return $Q$;
```

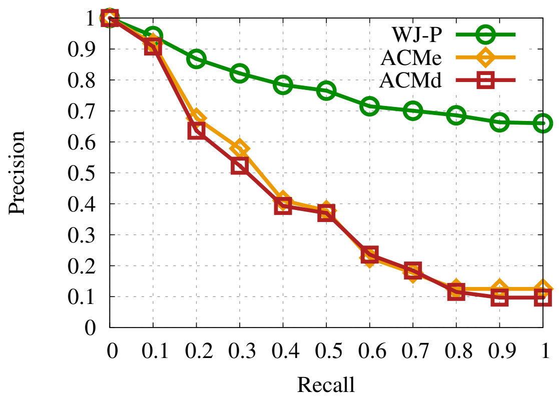
is within the qualifying hyper-ring defined by the pivots. The pertinence of t_y to the region convered by t_x is then checked in step 14-15, where an additional distance computation was performed. The steps 15-22 are similar to those presented in Algorithm 1, where κ elements are selected so the algorithm checks for possible replacements of the most similar pairs.

4 EXPERIMENTS

This section reports on experiments using our framework for near-duplicate image detection. The goal is to evaluate the proposed self range wide-join tech-



(a) Runtime



(b) Precision × Recall

Figure 4: Performance and quality analysis: the `Fire` dataset.

nique in terms of both the computational performance and the answer quality, targeting prioritizing those aspects as required for an emergency monitoring system.

4.1 Experiment Setup

We describe the results performed on a real dataset - `Fire` - composed of 272 images of fire incidents. Those images were obtained from an emergency situation simulation, held in an Industrial Complex. The dataset was previously labeled by domain experts and 25 distinct incident scenes were recognized. The images were submitted to the Color Layout (Kasutani and Yamada, 2001) extractor, which generated 16 features. The L_2 (Euclidean) metric was employed to evaluate the vector distances.

We compared our improved pivot-based self range wide-join (WJ-P, Algorithm 2) using 5 pivots with three other techniques. The first is the similarity wide-join with a nested-loop approach (NLWJ), that is the *self version* of the baseline found in the literature (Carvalho et al., 2015). The second method is the Adaptive Cluster with k-means (ACMe - Section 2) (Li et al., 2015). Also, once k-means is sensitive to outliers and often computes "means" that do not correspond to real dataset images, we generated a third method that is an ACMe variant replacing k-means with the k-medoids algorithm, calling it ACMd, in order to better analyze the answer quality. When necessary, the parameter ξ was set to retrieve about 1% of the total number of possible pairs.

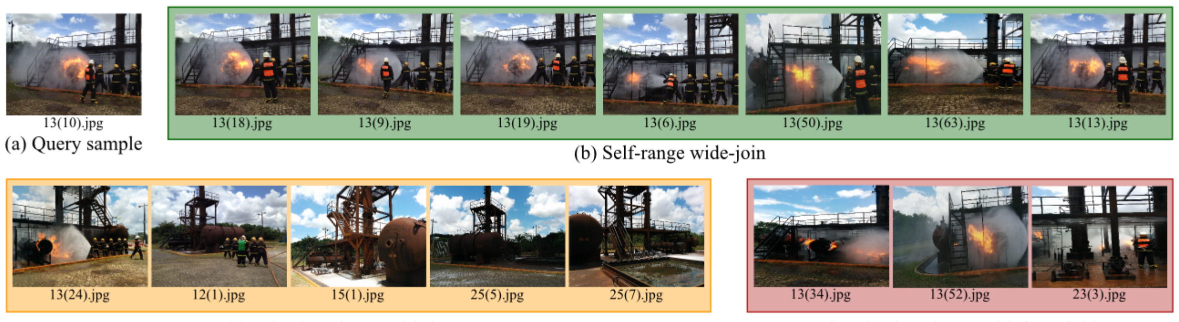
The experiments were executed in a computer with an Intel® Core™ i7-4770 processor, running at 3.4 GHz, with 16 GB of RAM under Ubuntu 14.04. All evaluated methods were implemented in C++. Each technique was evaluated with respect to both the total running time (Section 4.2) and the answer quality (Section 4.3), as follows.

4.2 Performance Experiment

Fig. 4(a) presents the total running time of the four approaches evaluated. The reported time corresponds just to the execution of the Near Duplicate Detection Module, as feature extraction was performed only once to provide data to the four methods. In this experiment, WJ-P was 44.45% faster than NLWJ. Also, both techniques based on self wide-join were 2 orders of magnitude faster than ACMe and 3 orders of magnitude faster than ACMd, whereas returning a high quality result set.

Such behavior occurs due to the fact that ACMe and ACMd cluster the dataset and recursively redistribute the elements following a hierarchical approach for the improvement phase, until the coherence of each cluster does not exceed a maximum value, computed during the process. In addition, to achieve the result, an improvement phase is usually required, which contributes to increase the computational cost of those approaches. Distinctly, the WJ-P performs a single pass computation that embodies the building and the improvement phases into an atomic, optimized operation.

Both ACMe and ACMd require a parameter k to execute their core clustering algorithms, the k-means and k-medoids, respectively. Nevertheless, they returned a number of clusters greater than k, because the clusters obtained in the building phase are subdivided according to their coherence values. Those techniques achieved the better results when k is set to values between 20 and 30. Unlike, the WJ-P method was able to achieve the result without the need of several executions in order to find out the better parameter adjustments.



(a) Query sample (b) Self-range wide-join

(c) Adaptive cluster with *k*-means (d) Adaptive cluster with *k*-medoids

Figure 5: Near-duplicates obtained by the three evaluated methods for the query center shown.

4.3 Answer Quality Evaluation

To analyze the answer quality, we evaluated how accurate is the result returned by the proposed framework. In order to enable fair comparisons among the distinct algorithms, we computed Precision and Recall ($P \times R$) curves. Evaluating $P \times R$ is a common technique used for information retrieval evaluation. Precision is defined as the rate of the number of relevant elements retrieved by the number of retrieved elements. Recall is given as the rate between the number of relevant elements retrieved by the number of relevant elements in the database. In $P \times R$ plots, the closer a curve to the top, the better the corresponding method.

Fig. 4(b) shows the $P \times R$ curves achieved by the three approaches. In this experiment, we did not consider the NLWJ approach because its result is the same also produced by the WJ-P and therefore both curves are identical, only varying their runtime. Our self range wide-join based on pivots achieved the larger precision for every recall amount. It was, in average, 35.14% more precise than ACMe and 36.78% than ACMd. After retrieving all relevant images in the dataset (recall of 100%), WJ-P consistently obtained 66.00% of precision in the result, whereas the competitor techniques achieved a maximum precision of 12.50%.

In order to show the obtained gain of precision, Fig. 5 samples the images considered as near-duplicates by the three techniques. Again, NLWJ is omitted once it computes the same result of the WJ-P, but the former is slower than the latter. For an image randomly chosen as query center (Fig. 5(a) - the 10th image with label 13), Fig. 5(b) shows the near-duplicates retrieved by WJ-P. As it can be seen, they have the same label and are in fact related to the query, recognizing even images with zoom and rotations.

Figs. 5(c) and 5(d) show the clusters obtained by the ACMe and ACMd, respectively. Both are the clusters where the query image (Fig. 5(a)) was allocated As it can be noted, both methods retrieved false positives, where the existence of false positives contributed to decrease the precision of ACMe and ACMd. Although ACMe theoretically leads to worse clusters than ACMd, as the means are not real images whereas the medoids are, the precision difference among both was in average only 1.63% (see Fig. 4(b)).

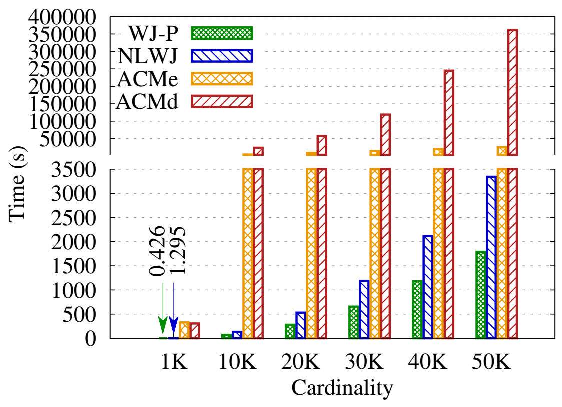
The superior quality of the answer of WJ-P when compared to the cluster-based methods shown in Fig. 4(b) is explained by the fact that the clusters are generated based on centroids or medoids seeds, and the remaining elements are allocated according to their distances to the seeds. The cluster elements are analyzed only in relation to the seeds, ignoring the relationship among themselves. This fact leads to some images that are distinct among them but considered similar to their seed, as represented in Figs. 5(c) and 5(d). In its turn, the self wide-join method establishes a “pairing relationship” among the elements, avoiding such drawback and increasing the answer quality, as also observed in Fig. 5(b).

Notice that Fig. 5 shows the images *spoted as near-duplicates* by each of the three techniques. According to the user interest, those near-duplicates can be either removed from the final answer of the framework so as to provide a more informative result set, or returned, allowing to analyze similar occurrences.

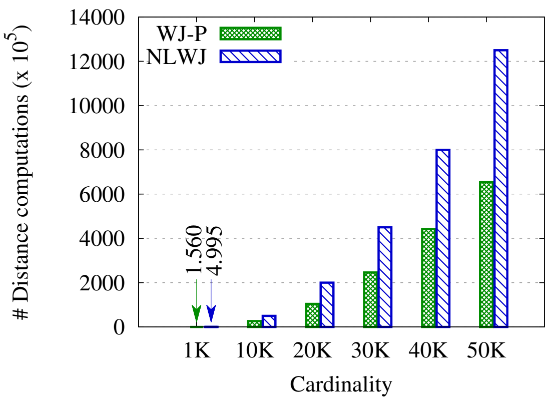
4.4 Scalability Analysis

The `Fire` dataset contains real images from an emergence scenario from the Rescuer Project, but it contains few images. So, we evaluated the scalability of our technique employing the `Aloi` dataset[2]. It contains images of 1,000 objects rotated from 0^o to 360^o in steps of 5^o(72 images per object, which we assume to be near-duplicates) giving a total of 72,000 distinct images. The Color Moment extractor (Stricker and

[2]<http://aloi.science.uva.nl> Access: Sept. 11, 2015.



(a) Runtime



(b) Distance computations

Figure 6: Scalability analysis: `Aloi` dataset.

Orengo, 1995) generates 144 features, which were compared using the L_2 metric.

For the scalability evaluation, we shuffled the `Aloi` images and varied the cardinality of the submitted data in several executions of our framework. Fig. 6(a) depicts the total runtime of each algorithm. The pivot-based self range wide-join (WJ-P) was in average 49.58% faster than NLWJ. Also, it was 96.25% faster than ACMe and 99.59% than ACMd, that is, it was correspondingly 2 and 3 orders of magnitude faster. For example, for a cardinality of 10,000 objects, WJ-P execution took 1.16 minutes and NLWJ took 2.20 minutes, while ACMe took 1.18 hours and AMCd took 6.61 hours.

Finally, Figure 6(b) compares both the similarity wide-join techniques (NLWJ and WJ-P) with respect to the number of distance computations performed to achieve the result. The pivot-based self range wide-join (WJ-P) executed at least 44.69% less distance calculations than NLWJ for a cardinality of 40K, but the greatest reduction of distance computations was observed for a cardinality of 1K, where WJ-P performed 68.75% less calculations. Nevertheless, it is important to highlight that both techniques obtained the same final result, but WJ-P was able to save computational resources in its processing.

Fig. 6 shows that as the cardinality increases, the cluster-based methods need to process more elements in the building phase. However, the coherence value is not used in this phase, so the next one (refinement phase) requires more iterations to subdivide the clusters and ensure that coherence is maintained. Distinctly, the wide-join perform a one-pass strategy. The increased cardinality turns the process more costlier, but in a less pronounced way as compared to the cluster-based ones. Moreover, to avoid performing distance calculations among every pair as occurs in NLWJ, the WJ-P prunes the number of comparisons, which also reduces the running time.

4.5 Experiment Highlights

In a general way, there are three main reasons explaining why the introduced self similarity range wide-join technique overcomes its correlates:

- *Single-pass computation*: usually, the near-duplicate detection is divided into two phases. The wide-join operator surpass the requirement for a refinement phase. As aforestated, such one-pass execution allowed to reduce the cost of the entire process in 2 orders of magnitude.
- *Efficient prune technique*: a prune technique based on pivots enables the proposed WJ-P algorithm to perform a reduced amount of element-to-element comparisons. The pivots delimit small regions of the space to be analyzed, allowing to discard several elements that surely will not compose the answer. Also, such strategy reduced the number of distance computations in about 44% in relation to the traditional nested-loop approach.
- *Similarity relationship between elements*: unlike the cluster methods, that computes the proximity of an element to a group, the self wide-join operator establishes a similarity relationship between each distinct pair of elements. It avoids the diversity found in two elements lying in opposite sides of a cluster, which increased the answer quality in about 35% in relation to the existing approaches.

5 CONCLUSIONS

In this paper we presented a framework model to detect near-duplicates using the similarity wide-join database operator as its core. We introduced the self range wide-join operator: an improved version of the wide-join that enables computing similarity by combining a relation to itself. We optimized the wide-join algorithm to scan the search space relying on pivots and using metric space properties to prune elements, which enabled achieving a large performance gain when compared to the existing solutions.

The experiments were executed using two real datasets. They showed that our proposed wide-join-based framework is able not only to improve the near-duplicate detection performance by at least 2 and up to 3 orders of magnitude, but also to improve the quality of the results when compared to the previous techniques.

The introduced technique is general enough to be applied over any dataset in a metric space, but we focused its application for an emergency-based application. When handling an emergency scenario, it is common that the eyewitnesses capture a large amount of photos and videos about the incident. Existing monitoring systems can benefit from those crowdsourcing information, aiming at improving decision making support. However, as the information increases, its elements tend to become too similar, so it is crucial to provide efficient techniques to properly handle near-duplicates.

As future work, we are exploring data distribution statistics and selectivity estimations for join operators in order to provide accurate definitions of the parameters required by the self-similarity range wide-join. We also intend to combine the images with their associated meta-data in order to further improve both the precision and the performance of near-duplicate detection.

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