A New Way to Detect Arrows in Line Drawings

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Abstract—A new way of detecting arrows in line drawings is proposed in this paper. We provide a set of criteria which are aggregated using the Choquet integral. These criteria are defined from the geometric properties of an arrow. Experimental results on two kinds of line-drawing documents show the interest of our approach.

Index Terms—Arrow symbol recognition, geometric properties, criteria aggregation, Choquet integral.

1 Introduction

Despite the large amount of technical documentation floating around, there have been relatively few accurate studies focused only on the detection of arrows in line drawings. It is well-known that such a symbol brings precious information for the understanding of the document under consideration (objects pointed out, associated text boxes, etc.). In many recognition systems, it is important to have an accurate and powerful operator related to the retrieval of such a symbol.

An arrow is a particularly important symbol in the set of symbols contained in documents. In order to spot it, efficient ways for recognizing symbols [1], or at least for identifying symbol signatures are required. The large variability of symbols encountered in technical drawings requires to use invariant descriptors for identification and recognition, and hence to find efficient and useful invariants [2]. Furthermore, approaches based on feature descriptors [3], [4] are sensitive to noise and are not robust to occlusions. A polygonal approximation of the objects [5] could be a solution to this problem. However, it induces loss of information, which may result in lower recognition rates. Dori and Velkovitch [6] have proposed a method for the location of dimensioning text from engineering drawings based on arrowhead recognition [7]. The results provided are interesting as in [8], but are application dependent and require arrows to have few distortions and to belong to a standard type as ISO or ANSI. In structural pattern recognition, field methods are usually based on graph matching to identify handwriting symbols in graphic documents [9], [10], [11]. In these approaches, some rules are defined from structural primitives of features with an associate cost function. Nevertheless, the methods are generally sensitive to noise and deformations. Valveny and Marti [12] have proposed a deformable template matching. Such an approach is based on a probabilistic model composed of lines. Nonetheless, this method is dedicated to symbols described by a set of segments and it is not easy to extend to manage binary objects. Moreover, the graph matching on large documents may require a lot of computing to take into account objects (subgraph matching) with occlusions.

A new way to detect arrows in line drawings is proposed. Our approach allows us to find an arrow even if parts of the symbol are occluded. The definition of a new arrow representation is proposed in Section 2. In Section 3, the identification step of arrows is presented. The aggregation of criteria and the general description of our method are given in Section 4. Experimental studies using real data are provided in Section 5.

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2 Arrow Properties

We provide in this section several properties which are necessary for the understanding of the paper. The Euclidean affine plane is referred to as a directional orthogonal frame $(O, \vec{x}, \vec{y})$. In this paper, a right built arrow is assumed to be the union of two geometric parts: an isocel triangle T—defined by three points $A_{(x_a,y_a)}$, $B_{(x_b,y_b)}$, and $C_{(x_c,y_c)}$—linked to a rectangle $R = (E_{(x_e,y_e)}F_{(x_h,y_h)}G_{(x_g,y_g)}H_{(x_f,y_f)})$. We set $c = d(A,B)$ and $a = d(A,C) = d(B,C)$, where d is the Euclidean distance (see Fig. 1). The description of an arrow is defined as follows:

[P1] *An isocel triangle (not equilateral) has a unique angle bisector, passing by C, which splits it into two symmetric parts. This bisector is also the median of the rectangle in an arrow.*

Now, let us consider point A. $Sec(a,c)$ is assumed to be the sector defined from the segments $[A,C]$ and $[A,B]$, which includes T from A. We set $\theta_B^A = \arctan(y_B - y_A / x_B - x_A) + k\pi$, with $x_B - x_A \neq 0$ and $k \in \mathbb{N}$, the angle between (A,B) and (O,x) and $\theta_C^A = \arctan(y_C - y_A / x_C - x_A) + k\pi$, with $x_C - x_A \neq 0$ and $k \in \mathbb{N}$, the angle between (A,C) and (O,x). As a triangle is a convex polygon, we have for any segment joining two points in T, every point on the segment must also lie within T. This is generalized to:

[P2] *Let us take the pencil of lines, noted $\mathcal{L}^A = \{D_\theta^A\}_{\theta\in[0,\pi]}$, including A. $V_A = \{I_A^\theta\}_{\theta\in[\theta_B^A,\theta_C^A]}$ is set as the definition of T from A in which I_A^θ is the segment beared by pencil of lines contained in $Sec(a,c)$.*

Let us note C_A the circle centered in A of radius $r = \max(a,c)$. All the segments I_A^θ, verifying [P2], are included in C_A (Fig. 1). The same method is followed to define V_B. V_C includes also the definition of R (that is using C_C centered in C of radius $r = \max(a, d(C,F))$). In this case, T and R are completely described ($(CEFGH)$ is convex). To summarize, V_A, V_B, and V_C represent the signatures which can be achieved by drawing pencils of lines from A, B, and C in the frame. In image processing V_A, V_B, and V_C are computed from raster data and afterwards compared with their theoretical approximation function. The definition of such functions is presented below.

Let us consider any triangle T', which consists of three points, not aligned: X_1, X_2, and X_3. X_1 is assumed to be the origin of the orthogonal frame and θ' and θ'' the angles described by the segments $[X_1,X_2]$ and $[X_1,X_3]$ from this frame. We also set $x = d(X_1,X_2)$ and $y = d(X_1,X_3)$. The aim is to define an other definition S_X of the signature V_X described above. Let f be the function allowing to define the new representation of $[X_2,X_3]$ from X_1 into V_X considering all the distances between the points of the segment and X_1.

The continuous function $S_{X_1}(\theta) : [\theta', \theta''] \rightarrow \mathbb{R}_*^+$, associated to V_{X_1}, is given by:

$$f(\theta, < x, y, \theta', \theta'' >) = \frac{x \cdot y \cdot \sin(\theta' + \theta'')}{x \cdot \sin(\theta - \theta') - y \cdot \sin(\theta - \theta'')}.$$

Let us now consider the points A, B, and C of the triangle T. The continuous function $S_A(\theta) : [\theta_B^A, \theta_C^A] \rightarrow \mathbb{R}_*^+$, associated to V_A, is: $S_A(\theta) = f(\theta, < a, c, \theta_B^A, \theta_C^A >)$.

The continuous function $S_B(\theta) : [\theta_C^B, \theta_A^B] \rightarrow \mathbb{R}_*^+$, associated to V_B—in this case, the orthogonal frame is referred to as $B(x_B, y_B)$—corresponds to: $S_B(\theta) = f(\theta, < b, c, \theta_C^B, \theta_A^B >)$.

The continuous function $S_C(\theta) : [\theta_A^C, \theta_B^C] \rightarrow \mathbb{R}_*^+$ is defined as follows:

If R is an empty rectangle: $S_C(\theta) = f(\theta, < a, a, \theta_A^C, \theta_B^C >)$, where $\theta_A^C \leq \theta \leq \theta_B^C$.

Else ($R \neq \emptyset$), five triangles are processed: $a' = d(C,E) = d(C,H)$, $a'' = d(C,F) = d(C,G)$ and the expression of $S_C(\theta)$ is given by (see Fig. 2):

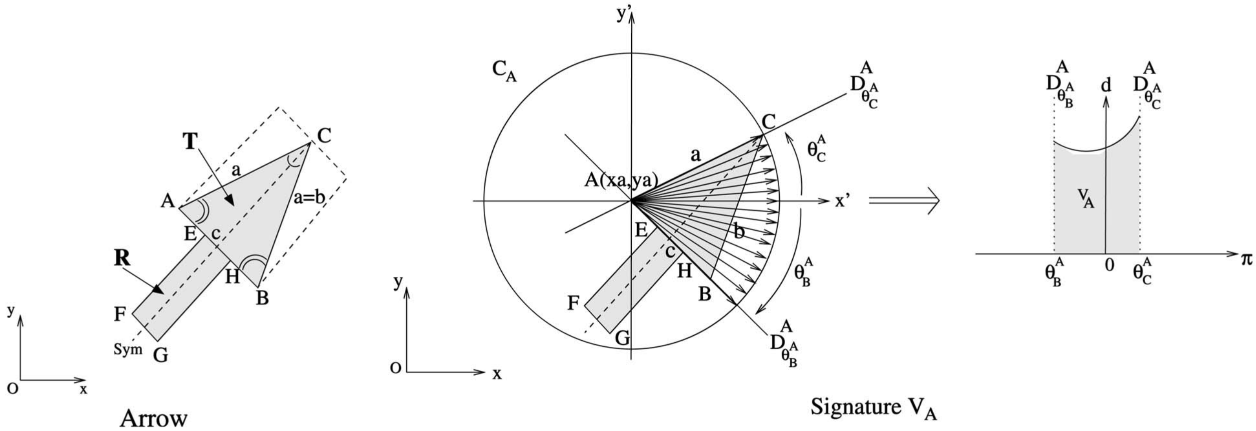


Fig. 1. Discrete signature of an arrow.

$$S_C(\theta) \rightarrow \begin{cases} \theta_A^C \leq \theta < \theta_E^C & f(\theta, < a, a', \theta_A^C, \theta_E^C >) \\ \theta_E^C < \theta \leq \theta_F^C & f(\theta, < a', a'', \theta_E^C, \theta_F^C >) \\ \theta_F^C < \theta \leq \theta_G^C & f(\theta, < a'', a'', \theta_F^C, \theta_G^C >) \\ \theta_G^C < \theta \leq \theta_H^C & f(\theta, < a'', a', \theta_G^C, \theta_H^C >) \\ \theta_H^C < \theta \leq \theta_B^C & f(\theta, < a', a, \theta_H^C, \theta_B^C >). \end{cases}$$

In the continuous case, it is easy to check that all the couples of signatures V_i and S_i are equivalent:

[P3] $V_A \Leftrightarrow S_A$, $V_B \Leftrightarrow S_B$, *and* $V_C \Leftrightarrow S_C$.

Now, we can consider the global signature S associated to an arrow as a union of signatures: Let t_π be a translation of π, then $S(T^{ABC}) = S_A \cup t_\pi(S_C) \cup S_B$ is a complete signature of T. Moreover, S is unique and we can deduce from [P3] the following definition: *Let t_π be a translation of π, then $V(T^{ABC}) = V_A \cup t_\pi(V_C) \cup V_B$ is a complete signature of T ($V \Leftrightarrow T$).*

So, the mathematical prototypes of signatures which define an arrow from three edges of an isocel triangle T are set.

If the shape of V is close to the one of S, we can assume that an arrow is recognized. Furthermore, we can draw the following properties based on the structure of an arrow to be checked. Since three angles specify a triangle only modulo a scale size [13], there is no overlap from the main parts of the signature:

[P4] $V_A \cap t_\pi(V_C) = V_B \cap t_\pi(V_C) = \{c\}$, $V_A \cap V_B \cap V_C = \emptyset$.

Since the triangle associated to the arrow is isocel:

[P5] $|V_A| = |V_B|$ ($|.|$ the area of the signature).

We consider now the symmetric aspect of the signature (see [P1]):

[P6] *There exists a symmetry, such that* $Symmetric(S_A) = S_B$.

[P7] S_C *is a symmetric map. That is* $\forall I_C^\theta \in V_C$, *there exists a unique* $I_C^{\theta'} \in V_C$ *such that* $Symmetric(I_C^\theta) = I_C^{\theta'}$. *There also exists a unique* I_C^θ *such that* $Symmetric(I_C^\theta) = I_C^\theta$.

At last, it is easy to show that the signatures V and S keep fundamental geometric properties, useful in a pattern recognition process such as scale, translation, and rotation.

3 Triplet Identification

Due to noise and digitalization, a binary test is not suitable to check the geometric properties of an arrow using real data. So, the definition of discrete criteria is needed. The location of triplets of points required for the calculation of such criteria is also presented.

3.1 Criteria

Let p be the number of bins, that is, the number of angles θ considered, of a signature. Each discrete signature is assumed to be circular, i.e.: $V^{p+i} = V^i$ (the signatures are 2π periodic). Let us now consider a numeric definition of five normalized criteria (Table 1).

The criteria Sym for symmetry is calculated to have an approximation which combine [P6] and [P7]. Sym is maximal when the angle t corresponds to the axis of symmetry of the signature. From [P5], the cardinality of V_A is close to the one of V_B (see criterion $Card$). An assessment of the degree of nonoverlap is required to check [P4] (see $\bar{Over}$). Let K be the common area carried out from the scans performed from A, B and C during the definition of V_A, V_B and V_C. The Heron formula [13] is used to calculate the area: $H = \sqrt{s(s-a)(s-b)(s-c)}$ where $s = \frac{1}{2}(a+b+c)$ is the semiperimeter. By definition, if the triplet describes a triangle in the image, the value of K must be close to the calculation of the Heron's formula H. The numerical signature V given by the triplet of points is matched with its theoretical

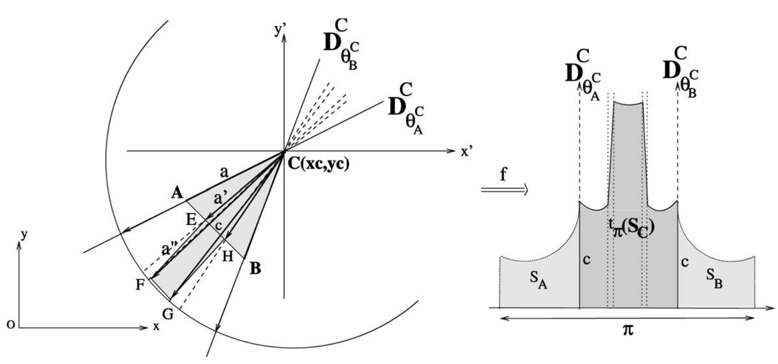
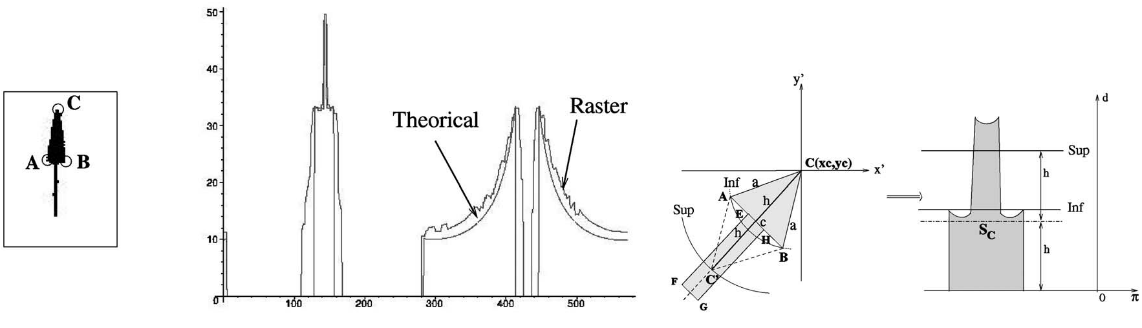


Fig. 2. Signature $S_C(\theta)$.

TABLE 1
List of Criteria to Be Checked

Criteria	Formula	Criteria	Formula
$C1$	$Sym = \max_{t \in [1,p/2]} \left\{ \frac{\sum_{i=1,p} \min(V^{t+i}, V^{t-i})}{\sum_{i=1,p} \max(V^{t+i}, V^{t-i})} \right\}$	$C4$	$Area = 1 - (K - H)/H$
$C2$	$Card = \min(\lvert V_A\rvert, \lvert V_B\rvert) / \max(\lvert V_A\rvert, \lvert V_B\rvert)$	$C5$	$Proto = D(V, \bar{S})$
$C3$	$\bar{O}ver = 1 - \frac{\sum_{i=1,p} \inf\{V_A^i, V_B^i, t_\pi(V_C^i)\} - 2 \cdot d(A,B)}{\sum_{i=1,p} \sup\{V_A^i, V_B^i, t_\pi(V_C^i)\}}$		



(a) (b)

Fig. 3. Signature estimation. (a) Signatures of a noisy arrow. (b) Rectangle estimation.

prototype S in order to check [P3] (see criterion $Proto$). We consider a discretization of S, denoted with $\bar{S}$, and D is a distance, denoted with $||.||_1$. Obviously, other formulae can be used to define such criteria. Nevertheless, the calculation of the features is essentially based on the maximizing of the classical Tanimoto index (min over max), which gives generally accurate results in pattern recognition applications and requires low processing time.

3.2 Cardinal Lists

Four scans of the plane from the four cardinal directions are enough to locate any point of the triplet because the triangle is supposed to be isocel and acute from the point C. Let $L = \{L_1, L_2, L_3, L_4\}$ be the four lists of points found. Let I_{ij} be the value of the point of coordinate (i, j) in an image I to be checked. A point added to a list L_u verifies this property: $L_u = L_u \cup \{(i, j)\}$ iff $I_{ij} = 1 \wedge \forall t \neq u, (i, j) \notin L_t$. A pencil of segments is drawn from each candidate point. All the points belonging to the segments and "seen"[1] by the selected point are removed to reduce the size of the lists. The image is restored after each scan. For efficiency reasons, Bresenham's algorithm [14] is used, as it is a fast method which minimizes errors in drawing lines on integer grid points.

3.3 Triplet Checking

The aim is to define a set of triplets to assess from the four lists of points. It is possible to consider all the configurations of points. Nevertheless, the processing time can be high using large documents and many configurations are inconsistent. So, we have imposed some basic constraints to drastically decrease the number of choices:

- Each triplet of points should be in the same connected component.
- Each point of the triplets should be "seen" by the others (or at least from one).
- The selected points belong to distinct lists.

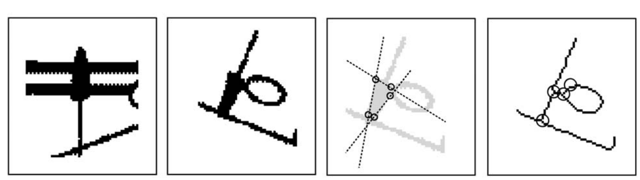
1. We mean by "seen" that the segment which links these two points remain entirely in the connected component, including the pairwise points.

When a triplet is set, three combinations of points are assessed using the Choquet integral (see Section 3) to determine which point is the more possible head of the arrow. If the triplet is recognized as an arrow, the points are removed from the cardinal lists (except for the occlusions).

3.4 Discrete Signature Estimation

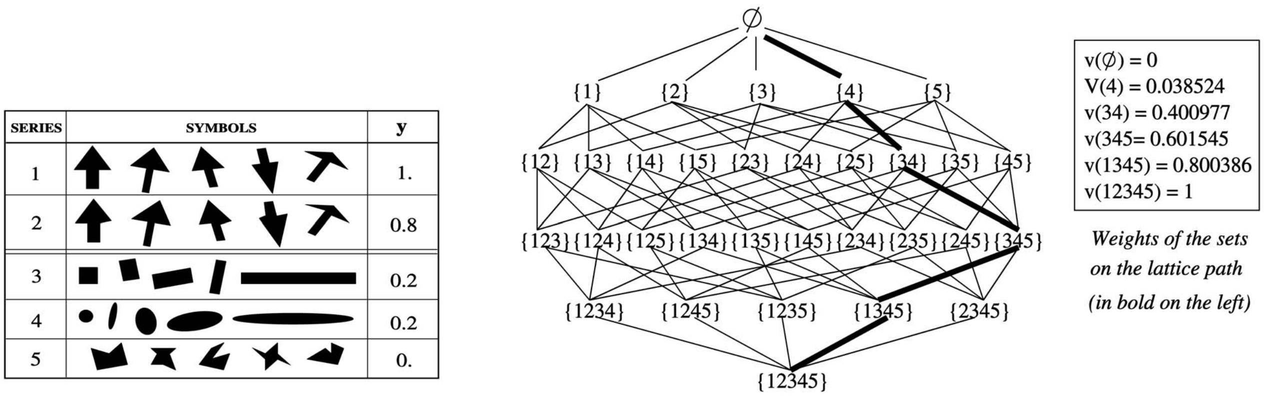
Since line drawings are often noisy, the starting areas corresponding to A, B, and C are adjusted within a circle with radius r (here, r is set to 1). We select the better starting points which maximize the main aspect of the signature. Fig. 3a shows a degraded arrow and the superimposed signatures reached from the local points found. The shape of the raster signature is close to its theoretical approximation.

The length of the spike (coming from V_C) corresponds to queue of the arrow which can be very long. We notice that the longer the rectangle is, the less the accuracy between the two signatures is. For the calculation of the criterion C5, we need to estimate the rectangle (EFGH). According to our model, an arrow without a rectangle is assumed to be a degenerated arrow and should have a lower recognition rate. For this reason, two boundaries (Inf and Sup) are set for the size of the rectangle (see Fig. 3b). If no rectangle is found, the estimation of the theoretical signature is assumed to be the same as that of a minimal rectangle signature (Inf) with a width of $[AB]/2$. The size of superior boundaries Sup is set by default as been twice the height of the triangle (see the rhombus $(CBC'A)$ on Fig. 3b).



(a) (b) (c) (d)

Fig. 4. Occluded arrows.



Series of samples and wished values

Lattice of the Fuzzy Measure

Fig. 5. Fuzzy measure defintion.

3.5 Robustness to Occlusions

When three edges of the triangle are clearly found from the cardinal lists step (in this case, there is no occlusion points in the vicinity of the three edges), our approach allows to find correctly an arrow even if parts of the symbol are occluded (see Fig. 4a). Additive data do not interfere with the general structure of the final signature.

In addition to the cardinal lists, we set a list of occlusion points to deal with degenerate cases. We consider an arrow as being degenerated when it is linked to a another symbol or a character or a line in a document (see Fig. 4b). The occlusion points are defined from skeletonization and pruning steps [15]. In this case, we consider more than three points (see Fig. 4c) and the new three edges of the triangle are defined from the intersection lines passing by points provided by the triplet checking step and the occlusion list.

4 Arrow Recognition

4.1 Choquet Integral

A first idea to merge the criteria defined previously may be to use a weighted sum. We can directly think that [C1], [C3], and [C5] are the main criteria, but which is the most important? Furthermore, all criteria should contribute as they are all defined from the basic structure of an arrow. Such a dependence cannot be taken into account using classical combinations. So, we have based our aggregation on the Choquet integral concept which is a generalization of Lebesgue integral and whose use was proposed by many authors (see [16], [17]). Let $N = \{1, 2, \ldots, n\}$ be a finite set of n criteria—$n = 5$ in our study—and let $\mathcal{A} = \{x^i\}_{i=1,l}$ be a finite set of l alternatives. Let v be a fuzzy measure on N such that [18], [19]: $v(\emptyset) = 0$, $v(N) = 1$, and $S \subseteq T \Rightarrow v(S) \leq v(T)$. Let us now consider an alternative $x^i = (x^i_1, \ldots, x^i_n)$ where x^i is an n-dimensional input vector containing the degree of satisfaction of object i with respect to criteria 1 to n [17]. $\forall v \in \mathcal{P}_N$, i.e., the power of N (number of subsets of N), the Choquet integral of $x \in \mathbb{R}^n$ is defined by:

$$\mathcal{C}_v(x) := \sum_{j=1}^{n} x(j)[v(A_{(j)}) - v(A_{(j+1)})],$$

where $(.)$ is a permutation of N such that $x(1) \leq \ldots \leq x(n)$ and $A(j) = \{(j), \ldots, (n)\}$ represents the $[j..n]$ associated criteria in increasing order.

TABLE 2
Importance of Criteria and Interaction between Them

Criterion	Sym	$Card$	$\bar{O}ver$	$Area$	$Proto$
Shapley	0.72	0.51	**1.03**	0.76	**1.97**

Interaction	Sym	$Card$	$\bar{O}ver$	$Area$	$Proto$
Sym	–	-0.05	**-0.45**	-0.14	**0.55**
$Card$	-0.05	–	-0.11	0.19	**0.88**
$\bar{O}ver$	**-0.45**	-0.11	–	**0.54**	0.02
$Area$	-0.14	0.19	**0.54**	–	0.41
$Proto$	**0.55**	**0.88**	0.02	0.41	–

Fuzzy measure
– Set of learning data
– Fuzzy measure computation
Arrow detection
– Calculation of cardinal lists
– List of triplets to be evaluated
For Each triplet
  For each combination of points of a triplet
    – Compute the criteria C1 to C5
    – Set λ the Choquet integral value
    If $\lambda >$ preset threshold
      – Label as arrow
      – Remove the points
    End If
  End For
End For

Fig. 6. Overall description of our method.

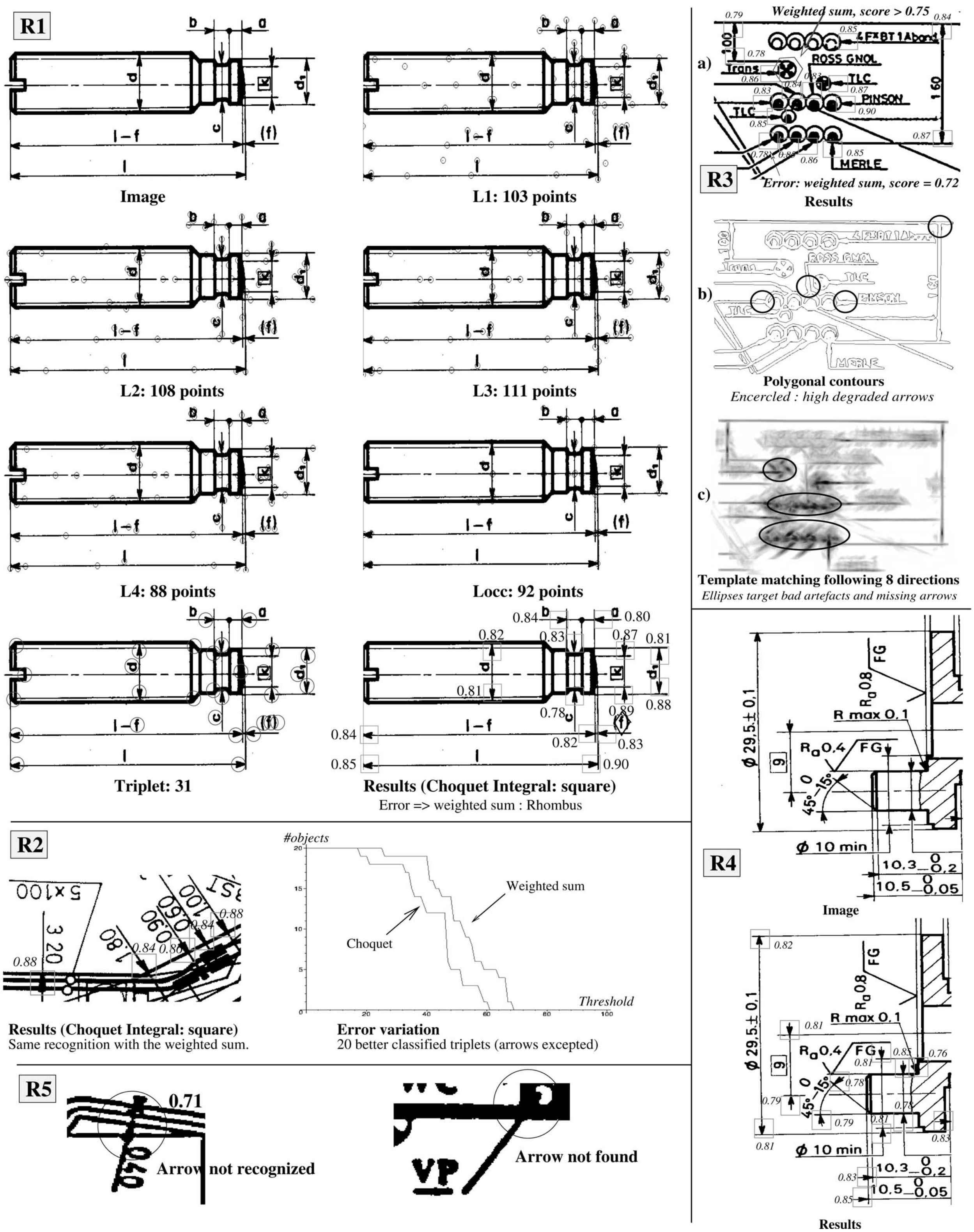


Fig. 7. Engineering drawings.

4.2 Fuzzy Measure

The calculation of the Choquet integral requires the definition of a fuzzy measure. That is, the assessment of any set v of $\mathcal{P}^N$ with $N = 5$ criteria in our study. By definition, $v(\emptyset) = 0$ and $v(\{1, \ldots, N\}) = 1$. There exists several ways to automatically set the $2^N - 2$ remaining values [16], [18]. The main problem is to give a value to the sets having more than three elements while keeping the monotonicity property of the integral. We consider here the definition of the fuzzy measure from a set of learning data. Fig. 5 presents five series of discrete samples. The value y represents the wished value after the calculation of the Choquet integral on all the examples of the series from the five criteria defined previously. Suppose that $(x^i, y^i)_{i=1,m}$ are m learning data where x^i is an alternative and y_i is the global evaluation of object i. Then, the best fuzzy measure is identified in such a way that $E^2 = \sum_{i=1}^{m}(C_v(x^i) - y^i)^2$ is minimized. Generally, the problem is translated to another minimization problem which is usually solved using the Lemke method. Grabisch [16] has shown that such an approach may be inconsistent using a low number of samples—ill-conditioned matrices—and the constraint matrix becomes parser when the set of alternatives grows causing bad behaviors of the algorithm. To overcome these problems, an optimal approach based on a gradient algorithm with constraints, which is an extension of the Muroshi and Sugeno's method [18], has been proposed in [20]. First, the fuzzy measure coefficients are set to a weighted sum. The modification of the weights is done following the path (fuzzy measure represented by a lattice of weighted sets as in Fig. 5) defined by the values of each learning data (criteria and input). Such an approach, used here, is fast and keeps the monotonicity even if the number of data is weak. The algorithm is described in the reference [20] and its implementation is easy.

An example is provided here to show the decomposition of the Choquet integral. The calculation of the criteria on the arrow of Fig. 3 gives the following alternative: $Sym = 0.87$, $Card = 0.85$, $\bar{O}ver = 0.94$, $Area = 1$, and $Proto = 0.88$. The calculation of Choquet integral gives a high score of recognition (see Fig. 5 for the weights of the sets):

$$C_v = 1. \cdot v(4) + 0.94 \cdot [v(34) - v(4)] + 0.88 \cdot [v(345) - v(34)] \\ + 0.87 \cdot [v(1345) - v(345)] + 0.85 \cdot [v(12345) - v(1345)] = 0.91.$$

Significant criteria as well as both negative and positive interaction effects can be established from the values of the sets. The importance of each criterion [16] is based on the definition proposed by Shapley in game theory [21] and puts back to fuzzy measure context by Murofushi and Soneda [22]: $\Delta(x_i) = \sum_{A\subset N-\{x_i\}} \lambda_X(A) \left[v(A \cup \{x_i\}) - v(A)\right]$ with $\lambda_X(A) = \frac{(|N|-|A|-1)!\cdot|A|!}{|N|!}$. The Shapley value is scaled by 5 (the number of criteria) and, so, an importance index greater than 1 describes an attribute more important than the average. Table 2 shows that the main criteria are $\bar{O}ver$ and $Proto$ (and not Sym!).

Such a definition has been extended in [22] to measure the interaction index between criteria as follows (values in $[-1, 1]$): $I(v)(x_i, x_j) = \sum_{A\subset N-\{x_i,x_j\}} \psi_X(A) I(v)(x_i, x_j|A)$ with:

$$\psi_X(A) = \frac{(|N| - |A| - 2)! \cdot |A|!}{(|N| - 1)!}$$

and

$$I(v)(x_i, x_j|A) = v(A \cup \{x_i, x_j\}) - v(A \cup \{x_i\}) - v(A \cup \{x_j\}) + v(A).$$

Both negative and positive correlations exist between criteria; in particular, between $Card - Proto$, $Sym - Proto$, $\bar{O}ver - Area$, and $Sym - \bar{O}ver$ (negative). According to the learning samples used to define the fuzzy measure, we set a threshold of 0.75 to consider if a triplet is recognized or not as an arrow after the calculation of the Choquet integral. To summarize, we give the overall algorithm of our approach in Fig. 6.

5 Experimental Results

Our approach has been applied on several types of line drawings and the obtained results are satisfactory. The method has required four seconds on the line drawings in Fig. 7 (R1) and 17 seconds in Fig. 7 (R4) without code optimization. The definition of the cardinal lists and the recognition step depend on the number of triplets and are linear in time processing. So, our approach is amenable to parallel processings. Moreover, the learning of the fuzzy measure (around 2"30s to learn the data) is independant of the application and performed only once.

Fig. 7 (R1) shows the application of our approach for an engineering drawing. The circles in images $L_1, L_2, L_3, L4$ corresponds to the points of the cardinal lists. The list of occluded points is referred to $Locc$. The image $Triplet$ provides the location of the triplets selected from the triplet checking step. The last image shows the detected arrows (identified by square boxes) and their associated score. To have an idea of Choquet integral interest, we have compared our approach with the classical weighted sum defined from the Shapley values. In this respect, we notice that the character f is recognized as an arrow (see the rhombus in Fig. 7 (R1)) using a classical weighted sum. The graph given in Fig. 7 (R2) shows the error rate of symbols classified as arrow. We notice from the graph that the aggregation is more discriminant using Choquet integral rather than the classical weighted sum. Such a result is confirmed by the experiment in Fig. 7 (R3a) where several symbols are misclassified or not recognized using the weighted sum. Fig. 7 (R4) shows the robustness of our approach on other distorted arrows. We notice that when the data are too noisy or when the arrows are too thin or very occluded, our method will obviously provide less accurate results (see Fig. 7 (R5)). We have also compared our approach with polygonal and template matching approaches. To better vizualize the problem, the correlation image is provided in Fig. 7 (R3b). Black areas correspond to a high correlation. We can remark that, in many configurations these approaches do not work (see the elements encircled in Fig. 7 (R3b and R3c).

6 Conclusion

In this paper, we have shown that the definition of angular and theoretical signatures and the aggregation of geometric criteria using the Choquet integral allow to achieve a robust detection of arrows. Currently, we focus on a subpixel definition to decrease the aliasing resulting from Bresenham's algorithm in order to increase the accuracy of our method. The extraction of text boxes in line drawings from the set of detected arrows is also under consideration. Finally, we want to generalize our approach to other families of symbols having well-known geometric properties.

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