ROAD SIGN RECOGNITION USING A HYBRID EVOLUTIONARY ALGORITHM AND PRIMITIVE FUSION

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ABSTRACT:

We present an algorithm to detect and recognize road signs from embedded terrestrial images. We argue that the most important process in such algorithms is the fine detection which isolates object shape in images. After this step, recognition can be processed by simple normalized template matching. We then use a hybrid evolutionary algorithm capable of performing the fusion between colour and edges detection. This hybrid approach associates a stochastic process and a local deterministic error minimization to increase the precision and improve the repeatability of the convergence by eliminating certain unpredictable processes such as mutation. Primitive fusion brings precision and decreases the necessary number of iterations (about 5 times faster) required to optimize the influence of every primitive during the algorithm execution. We present this algorithm and show that we can use a final template matching in a simple way.

1 INTRODUCTION

Over several decades, digital technology has become a crucial tool and data ownership has become the key to knowledge. Digital data allow us to understand our environment and optimize its management whatever the application. Digitalization tools have thus become a real need.
Road network data is a particularly pertinent example since such networks represent huge responsibilities for their administrators when roads contain defects and incoherence which can provoke accidents. There is therefore a growing trend to the digitalization of knowledge of road networks and their equipment to improve management, security and, in the near future, lead towards autonomous navigation in urban road environments using advanced maps.
Consequently, laboratories and companies are interested in developing mobile systems to acquire digital descriptions of roads. These systems, called mobile mapping systems (*MMS*), produce huge quantities of data based on multiple sensors such as cameras and lidars. These data are necessary but, nevertheless, insufficient because they do not bring semantic knowledge about the environment. Acquisitions are still limited to small areas to prevent non-exploitable quantities of data being acquired from *MMS*. For this reason the current aim of many researchers is to develop robust algorithms to automatically recognize objects by image or signal processing, and to limit the manual treatment by human operators.
Algorithms of shape recognition by image processing can be generally separated in two distinct tasks : detection and recognition. We think that the most important task is detection which consists in producing smart samples of the image data. Afterward, these samples can be compared to a database of known object images. We therefore developed an algorithm able to determine the affine mapping between the image of the object and real spatial configuration of the object. In this way we are able to obtain a quasi-perfect front view of the object in a sample image. The sample image is then used in a simple Normalized-Grayscale correlation to recognize the correct object.
To do this, we oriented our research towards hybrid evolutionary strategies (Hybrid-*ES*). Evolutionary Algorithms (*EA*) are stochastic processes for optimization problems regrouping genetic algorithms (*GA*) and *ES* : biological metaheuristics simulating natural phenomena such mutation and natural selection, keeping precise scheme. On the other hand, some algorithms use deterministic methods to match two different shapes like, for example, the iterative algorithm *ICP* for Iterated Closest Point introduced by (Besl and McKay, 1992).
We propose to combine both approaches and to fusion edge and colour extraction to improve precision and convergence speed. In what follows we start with a rapid overview of related work dealing with road sign recognition and general shape recognition, we then recall some previous knowledge about deformable templates and finally we present our algorithms, results and conclusion.

2 RELATED WORKS

Road sign recognition is a vast topic in image processing. Initially, accumulative methods such (Hu et al., 1998) and (Pedersen, 2007) seem interesting to detect manufactured shape in images. These methods permit the extraction of polygon centres, lines or circles thanks to statistical processes. Some of them used these accumulative methods to the particular application of road sign recognition application such as (Belaroussi and Tarel, 2009) and (Barnes et al., 2008). The complexity of the search increases with the complexity of the polygon we are looking for, and in the end, the accumulation space becomes very difficult to sample. Besides, these methods show low tolerance to strong affine transformations in the image (circle easily becomes ellipse for example).
On the other hand, (Arlicot et al., 2009) proposes to pre-detect colour areas and to filter these connected components to find ellipse equation using a RanSaC algorithm. This algorithm is only available for circular road sign also it seems to be robust to spatial transformation.
The seminal works of (Jolly et al., 1996) use a Simulated Annealing algorithm (*SA*) using deformable templates to detect vehicle's profile and use motion detector to help the convergence of the system. Extending this approach based on deformable template, M.Mignotte proposes three kinds of optimization algorithm to detect particular shadows in sonar images : simulated annealing,

gradient-descent and a genetic algorithm (*GA*). He shows that *GA* is the most efficient method, however, the algorithm requires 20 to 120 iterations for a population size about 100. With the same idea, (De La Escalera et al., 2004) compares *GA* and *SA* to detect road signs, and a simple normalized correlation score to recognize road signs from an image database. Roughly 50 iterations are required to find translation, rotation, scale and stretch parameters with 101 individuals. Dealing with biological metaheuristics, (Siarry, 2007) and (Deneche et al., 2005) propose different methods for shape recognition using an Evolutionary Algorithm (*EA*), clonal selection (*CS*) and Particle Swarm Optimization (*PSO*).
It can be observed that these evolutionary algorithms and metaheuristics are very efficient in shape recognition but that they suffer from other drawbacks : unpredictable processes (such as mutation, crossover *etc.*) can provoke hazardous behavior during population evolution (*i.e.* several computations on the same image can lead to different results) which require large numbers of iteration for the problem to be avoided. It what follows we show that by hybridizing the evolutionary algorithm to carefully combine colour information (lower noise sensitivity) and edge information (greater precision), we can constrain convergence, improve process repeatability and reduce the number of required iterations.

3 PREVIOUS KNOWLEDGES

To understand our approach, we need to introduce some notation. Our algorithm use deformable templates and primitives extraction based an edge and colour detection. Each template is then associated to a spatial configuration necessary to explain affine mapping. The primitives are used by the algorithm to find the best {template-configuration} couple based on a score that we propose below.

3.1 Deformable template

We use the term deformable template to describe a mathematic shape P defined by edges and regions. This template can be a point-cloud which could be transformed relative to configuration. Concerning the conditions in which our template will be used, it seems justified that we have to use affine transformations based on 6 different parameters : Scale s, Translation t_u and t_v, Rotation θ, Stretch e and Skew d. This affine transformation is associated to a transformation matrix with respect to a configuration vector $\mathbf{a} = (theta, s, t_u, t_v, e, d)^t$:

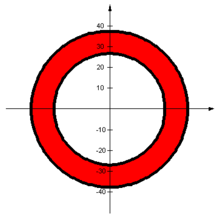
$$T_{\mathbf{a}}(\mathbf{x}) = \begin{pmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{pmatrix} \begin{pmatrix} 1 & d \\ 0 & 1 \end{pmatrix} \begin{pmatrix} s & 0 \\ 0 & se \end{pmatrix} \mathbf{x} + \begin{pmatrix} t_u \\ t_v \end{pmatrix} \quad (1)$$

We choose to show our results for a red road sign. Figure 1 represents both templates we use to fine-detect these red road signs. A template is described by two different classes : black points belong to edges, red points belong to colour region (i.e. red in this case). We note this subset of points respectively Pe and Pr. A template which is transformed w.r.t a configuration vector $\mathbf{a}$ will be written as :

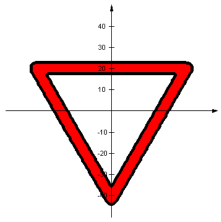
$$P_{\mathbf{a}} = \{p(\mathbf{a}) = T_{\mathbf{a}}(p) \quad \backslash \quad p \in P\} \quad (2)$$

3.2 Primitives extraction

In order to compare our results to those presented in (Siarry, 2007), we use the same colour extraction algorithm. Dutilleux & Charbonnier present, in their book (chapter ten), three kinds of biological metaheuristic applied to road sign detection. We



(a)



(b)

Figure 1: Templates used to detect (a) interdiction road signs and (b) danger road signs

retain the same extraction to be able to compare our detection algorithm to theirs. This extractor is a multi-criterion extraction. The method uses non-normalized colour component and we need no intermediate calculations because the first criterion imposes a condition on $r = \frac{R}{R+G+B}$. Then, we obtain an image $C_r(I)$ from which every white pixel corresponds to non-red pixel and every black pixel corresponds to red pixel of the original image as shown in figure 2. More details can be found in (Siarry, 2007).

The second primitive concerns edge extraction. This algorithm is simply based on a gradient calculation in every direction of the original image. We then calculate the thresholded image of the gradient magnitude and we remove every local minimum to deduce edges. In a Similar way to the colour extraction, black pixels represent edges as shown in figure 2. If I is an image, ∇I represents the gradient image and $\|\nabla I\|_T$ the edge image using a threshold T.

3.3 Distance transform

Felzenszwalb et al. describe an algorithm which calculates what we call the Distance Transform (DT) of an image ((Felzenszwalb and Huttenlocher, 2004)). The DT of a binary image (i.e. every pixel belongs to only two possible classes) gives an image D_I where the pixel value is the distance between itself and the closest pixel of I belonging to the right class. The algorithm proposed in (Felzenszwalb and Huttenlocher, 2004) was chosen because, unlike the one proposed in (Borgefors, 1986), the calculation is not an approximation of the distance but the real euclidean distance. For our application, we chose to work with exact distances even though the approximation method is three times faster.

$$I_0 = \{q = (u, v)^t \quad \backslash \quad I(q) = 0\} \quad (3)$$

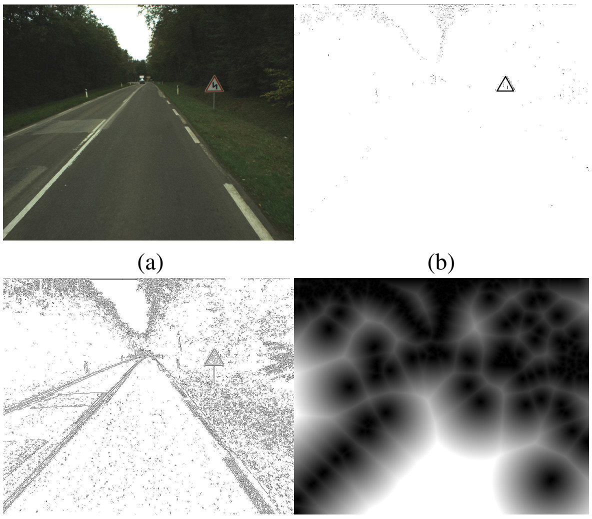
The expression of the DT of an image I with respect to a class I_0 then becomes :

$$D_I(p) = \min_{q \in I_0} \|p - q\| \quad (4)$$

3.4 *ICP* Algorithm

The *ICP* algorithm (or Iterated Closest Point) is an iterative algorithm which is made for determining linear transformation between two similar point clouds. The number of points in each cloud is not necessarily the same. An excellent descritption of this algorithm is presented in (Druon et al., 2006) : for two different sets of points $\{S\}$ and $\{D\}$, we define the error ϵ between the sets. This error to be minimized with respect to the transformation T and is calculated as the sum of the distance between matched points from set $\{S\}$ and $\{D\}$ (Cf. 5).

$$\epsilon = \frac{1}{N} \sum_{i=1}^{N} \|d_i - Ts_i\|^2 \quad (5)$$



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

Figure 2: 1826-th image of CD3 sequence. (a) Original image. (b) Red colour-extraction image. (c) Edge-extraction image. (d) Distance transform image of image (b).

This error measure must match every point of $\{S\}$ with closest point of $\{D\}$. Fitzgibbon in (Fitzgibbon, 2003) proposes a method to improve the *ICP* algorithm. This algorithm is an iterative method to calculate the new configuration using a Newton-Gauss algorithm. For a deformable template P defined as a set of points, we define, with respect to a configuration vector $\mathbf{a}$ and an image I composed by a class I_0, the error function :

$$E(I, P, \mathbf{a}) = \sum_{p \in P_{\mathbf{a}}} \min_{q \in I_0} ||q - p||^2 = \sum_{p \in P_{\mathbf{a}}} {D_I}^2(p) \qquad (6)$$

Fitzgibbon shows that the new configuration $\mathbf{a} + \mathbf{da}$ minimizes this error function and gives the relation :

$$\mathbf{da} = -(\mathbf{J}^t \mathbf{J})^{-1} \mathbf{J}^t \mathbf{e} \qquad (7)$$

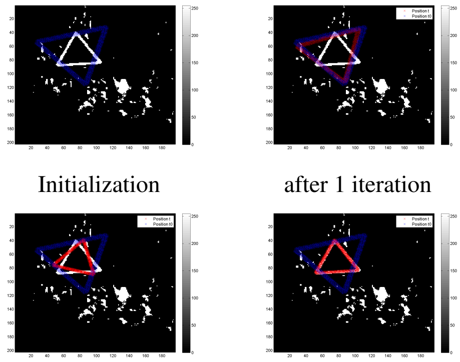
Where $\mathbf{J}$ represents Jacobian matrix of the residuals vector equal to $\mathbf{e}(I, P, \mathbf{a}) = (D_I(p_1(\mathbf{a}))...D_I(p_N(\mathbf{a})))^t$. The calculation time to estimate Jacobian matrix would be prohibitive even if we are not interested in real time processing. However, Fitzgibbon describes a method to improve the Jacobian matrix calculation in image processing which is based on Distance Transform.

$$\mathbf{J} = \{J_{ij}\} = \left\{ \begin{pmatrix} \frac{\delta D_I}{\delta u}(T_{\mathbf{a}}(p_i)) \\ \frac{\delta D_I}{\delta v}(T_{\mathbf{a}}(p_i)) \end{pmatrix} \cdot \begin{pmatrix} \frac{\delta T_u}{\delta a_j}(p_i) \\ \frac{\delta T_v}{\delta a_j}(p_i) \end{pmatrix} \right\} \qquad (8)$$

See (Fitzgibbon, 2003) for full details. Figure 3 shows an example of the convergence step.

3.5 Evolutionary algorithm

Evolutionary algorithms represent several families of algorithms such evolution strategy (*ES*), genetic algorithms (*GA*) and differential evolution algorithms. A reference application is often cited when we deal with *EA* : the travelling salesman problem consists in finding the shorter path we have to follow in the case we have to pass through N knots. However, Thomas Bäck reminds us in (Bäck, 1996) that the *EA* is primarily an algorithm used in optimization problems and proposes a simple example : let consider a parameters vector $\mathbf{a} \in \mathbb{R}^n$, an observable set of points $\{(x_1, y_1), \ldots, (x_N, y_N)\}$, and assume the existance of estimator $\hat{y}(\mathbf{a}, x)$ to describe the relation between y_i and x_i. The least mean square optimization can then be written as :



Initialization — after 1 iteration — after 30 iterations — after 40 iterations

Figure 3: Different steps of *ICP* algorithm. In blue, initial position of the triangle template, in red the different position of the template after 1, 30 et 40 iterations.

$$f(\mathbf{a}) = \sum_{i=1}^{N} (\hat{y}(\mathbf{a}, x_i) - y_i)^2 \qquad (9)$$

Bäck indicates that the general scheme of an evolutionary algorithm for an initial population Po is :

- Initialize a population $Po(0) = \{\mathbf{a}_1(0), \ldots, \mathbf{a}_\mu(0)\}$
- Evaluate $Po(0)$ w.r.t its environment
- While $\iota(Po(t)) \neq true$ do :
  1. Recombine a new population from previous one
  2. Mutate the population
  3. Evaluate every individual
  4. Select best individuals
  5. $t \leftarrow t + 1$

We see here that ι function is a termination criterion. Generally, this condition is based on the evaluation function which gives every individual a kind of adaptability score with respect to the environment. We note the analogy with the previous *ICP* algorithm in research of minimizing error on every iteration.

4 HYBRID ALGORITHM

Considering (Siarry, 2007), (Mignotte et al., 2000) or (De La Escalera et al., 2004), we can see that biological metaheuristics are efficient for shape recognition in image processing. We here propose a fusion of an *ES* and deterministic approach based on a local *ICP* algorithm, along with the combination of two different primitives, colour and edge, to improve the quality of convergence. The deterministic approach improves quality and convergence speed, while *ES* helps avoiding local minima.

4.1 Termination criterion

The termination criterion is based on a maximum number of iteration and on a score which represents the quality of an individual w.r.t a configuration in an image. As shown in (Siarry, 2007), the edge-based score is more discriminating than the region-based score calculated from colour detection for example. They propose edge-based score, inspired by (Jolly et al., 1996), which depends on the distance from template's edges to image's edges, weighted by the magnitude of the oriented gradient difference $\varphi_p - \gamma_p$. φ_p and γ_p represent the orientation of gradient of template and image w.r.t point p respectively. However, we observed that the bigger an object's representation in an image, the harder it is for the template to converge. This is logical considering that the accumulated distance can easily become large when we work on bigger objects while the template is relatively fine-positioned. For this reason, we use a similar score but we integrate the scale s of the template to be more tolerant of large distances on bigger templates. The score is calculated to be in the interval $[0, 1]$.

$$S \propto \sum_{p \in Pe_{\mathbf{a}}} exp\left(\frac{-D_{\|\nabla I\|_{Tc}}(p)}{s}\right)|cos(\varphi_p - \gamma_p)| \qquad (10)$$

Consequently, we deduce the edge-based error $\epsilon_e = 1 - S$ which corresponds to perfect matching. This error is important because we use this criterion to auto-adapt the forces repartition in primitives fusion.

4.2 Primitives fusion

Now let us consider a population of individuals which represents the association of deformable templates and spatial configuration of 6 parameters $(\theta, s, t_u, t_v, e, d)^t$ in an given image. Every template is initially associated to a configuration and every individual is able to converge to minimize its local error thanks to a deterministic process described in 3.4. This ability depends on error which, itself, depends on particular primitive. For example, the error in relation to the edge extraction of an image I would be $E(Ie, Pe, \mathbf{a})$. In fact, we are able to write this error for every primitive we wish. Each error would be associated to infinitesimal shift $\mathbf{da}$ which can be used in addition to the configuration vector $\mathbf{a}$. In default case, we could perform a simple linear combination of infinitesimal shifts :

$$\mathbf{a}_{t+1} = \mathbf{a}_t + \frac{1}{\sum_{k=e,r} \alpha_k}\left(\sum \alpha_k \mathbf{da}_k\right) \qquad (11)$$

However, if we look the extraction result, we can easily understand that colour extraction is not locally smart due to the Bayer filter of the camera and local colour aberration. On the other hand, colour extraction presents only few possible areas because red regions are unusual in natural environments. Edge extraction is locally considerably more precise than colour extraction but has the disadvantage of being very noisy. This is simply due to the fact that many objects in an image scene possess edges. We reasoned that we could intelligently find a dynamic relation between infinitesimal shifts to improve both the number of iterations and the convergence precision. Consequently, we think that an individual should first use the colour-based primitive to rapidly converge around one area and then use the edge-based primitive to converge with precision.
Considering the only red road sign detection application, we obtain the following relation :

$$\mathbf{da} = \alpha_\tau(\epsilon_e - \epsilon_{ref})\mathbf{da}_e + (1 - \alpha_\tau(\epsilon_e - \epsilon_{ref}))\mathbf{da}_r \qquad (12)$$

Where α_τ is a function defined as :

$$\alpha_\tau : \left\{ \begin{array}{lll} [0,1] & \rightarrow & [0,1] \\ x & \rightarrow & \alpha_\tau(x) = \frac{1}{1+e^{\tau x}} \end{array} \right. \qquad (13)$$

This function α_τ allows to auto-adapt the influence of primitives during an individual's life time. This individual will be more influenced by colour extraction when its error is high, and conversely, the influence of a template's edges will be higher when the error is low. We will show the advantage of this function in section 5.

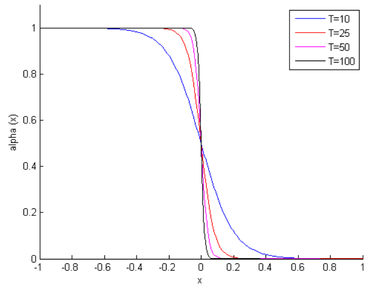


Figure 4: Function α used to change influence from primitives along iteration

4.3 Population & initialization

As well as the proposition in (Siarry, 2007), we choose to initialize our population using connected colour extraction components. As stated previously, these connected components are not perfect because colour extraction is not a noiseless process. We therefore decided to use random variables to initialize the population around connected components. We take N_p to denote the number of templates in our population and N_{cc} to denote the number of connected components in our image associated to region of interest $((u, v)^t, w, h)$. We take 5 random variables K, Θ, S, U and V which follow a uniform distribution on $\{1, ..., N_{cc}\}$, and a normal distribution $\mathcal{N}(0, 0.1)$, $\mathcal{N}(1, 0.2)$, $\mathcal{N}(0, 0.2)$ respectively. Our initialization process is :

$$\mathbf{a}_k, \quad k \in [1, N_p] \left\{ \begin{array}{ll} \theta & = \Theta \\ s & = S \times \frac{\min(w_k, h_k)}{2*R} \\ (t_u, t_v)^t & = (u, v)_k^t + (U \times w_k, V \times h_k)^t \\ e & = 1 \\ d & = 0 \end{array} \right. \qquad (14)$$

Where R is the default current template size.

5 RESULTS

We have used the same image database as in (Siarry, 2007). We used 3436 images in this database, grabbed using a front-view camera embedded in a vehicle. This database was used to evaluate different pre-detection algorithms in (Foucher et al., 2009). We found 18 red triangular road signs on 48 images. Figure 2 shows one of these road signs. Every primitive (edge and red extraction images) is calculated from every original image but we do not try to detect road signs if there are no connected components with an area of more than 100 pixels. The population consists of 20 individuals per template. We note that the complexity of this algorithm is linear with respect to the population size. Recombination of individuals is not used because we observed that this brought no improvement. We therefore just used natural selection by removing the 8 worst individuals from the population at each iteration and we re-initialized 8 brand-new individuals.
The first result to remark is the very good rate of convergence, due in part to edge-based score calculation. Figure 5 shows the "Receiver Operating Characteristic" (ROC) curve representing the true positive detection rate with respect to the false positive detection rate. Each point on this curve represents a different decision threshold based on ϵ_e. The oriented gradient-based score

perfectly discriminates road signs from noise compared to simple gradient-based score.

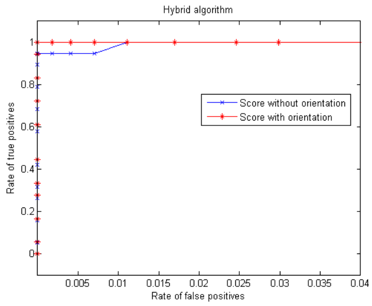


Figure 5: ROC curve for our algorithm applied to database *CD3* and using two kinds of score calculation

To illustrate the interest of primitives fusion, we used the same image database which we processed using different values of the parameter ϵ_{ref}. This parameter changes the influence of primitives with respect to the error ϵ_e. The lower the value of ϵ_{ref} (closer to zero), the later the appearance of edge primitive influence in the convergence process. This means that for low values of ϵ_{ref}, edge primitive effects lose their influence and the precision of convergence should be lower. On the other hand, if we use higher values for this parameter, we lose in efficiency and an individual would require more iterations to match an object. This phenomenon is observed in figure 6 which shows the mean number of iterations required (generations) for the best individual to converge (minimum error) on a road sign, and the mean error that the best individual reaches. We note that if we choose a large value for ϵ_{ref}, the mean of number of generations is about 3 times higher. We therefore choose a value of ϵ_{ref} around the point of the convergence point of the curves. The algorithm needs around 15 iterations with 20 individuals to achieve a very precise convergence compared to the needed 50 iterations with 100 individuals for (De La Escalera et al., 2004). In order to show the precision

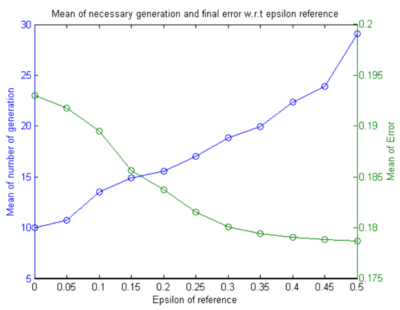


Figure 6: Mean of number of generation and mean of final error of best idividual w.r.t ϵ_{ref}

of the convergence, figure 7 deals with different views of samples which come from original images. The fine-detection algorithm found an ideal couple {template, configuration} to inverse transform the corresponding area into front view colour images of (80x80) pixels which we call “samples”. These samples can easily be used in Brightness and Contrast Invariant (BC-invariant) template matching to identify the sample in a road-sign database. We implemented simple BC-invariant template matching to calculate a correlation score for each colour band. We calculate the sum of square of these three scores to obtain the general correlation score. Examples are shown in figure 9.

Figure 7: Some samples of road sign picked up from images thanks to fine convergence of hybrid algorithm. These samples can be easily used in correlation algorithm.

Figure 8: Database of red triangular road signs used in BC-invariant template matching.

6 CONCLUSION

We present a real optimized method to fine-detect road signs in an image scene. Our first contribution consists in combining two different approaches : the first is an evolutionary algorithm which allows us to make global optimizations thanks to stochastic processes, the second is a deterministic algorithm used to minimize the local configuration error of a deformable template which improves the convergence precision and the process repeatability. The definition of a greater number of templates permits detection of other shapes such as circular road signs without no change in the algorithm (figure 9). Our second contribution is to combine the colour information and edge information to obtain an autoadaptive convergence and to fine-detect objects with high precision with a small number of iterations. While (De La Escalera et al., 2004) presents an analog genetic based algorithm where about 100 individuals per template are required and more than 50 iterations to get their best results, our algorithm is able to converge in less than 10 generations. Compared to work in (Siarry, 2007) where different *EA* are used to minimize configurations of 4 parameters, we are able to manage a 6-dimensions configuration vector which enables us to extract precisely road signs with strong spatial tilt such as the temporary road sign in the first image of figure 9. The associated sample is the first one on figure 7 where we observe that the road sign perfectly matches the image’s dimensions. Finally, we have shown that we can use simple Brightness and Contrast invariant template matching to recognize every sample that the fine-detection algorithm produces.

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Figure 9: Road sign recognition using BC-invariant template matching after fine-detection algorithm.