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LEARNING TO DETECT GOOD IMAGE FEATURES

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LIST OF SYMBOLS AND ABBREVATIONS

SIFT	Scale Invariant Feature Transform
FREAK	Fast REtinA Keypoint
BRIEF	Binary Robust Independent Elementary Features
TILDE	Temporally Invariant Learned DEtector
AMOS	Archive of Many Outdoor Scenes
ANN	Artificial Neural Network
CNN	Convolutional Neural Network

RIASSUNTO

Gli algoritmi di feature detection allo stato dell'arte sono stati pensati per estrarre determinate strutture da immagini e per raggiungere un alto livello di ripetibilità dei punti salienti, ossia per rilevare gli stessi punti in immagini sottoposte a determinate trasformazioni. Tuttavia, questo criterio non garantisce che i punti trovati saranno ottimali durante la fase successiva: il matching. L'approccio sviluppato all'interno di questo lavoro è volto all'estrazione di punti salienti che massimizzino le prestazioni del matching in accordo con il tipo di descrittore scelto. Per fare ciò, un classificatore è stato addestrato utilizzando un insieme di descrittori "positivi" e "negativi" estratti da immagini sottoposte a trasformazioni definite in precedenza. Prima di tutto, le immagini utilizzate per l'addestramento sono state campionate e confrontate analizzando le distanze tra i descrittori ottenuti attraverso uno specifico procedimento. Successivamente, si è creato l'insieme dei campioni positivi prendendo i descrittori relativi a quei punti che hanno dato corrispondenze corrette durante la fase di matching. Contrariamente, punti campionati casualmente e sufficientemente distanti dagli esempi positivi sono stati classificati come negativi. Infine, i descrittori calcolati in corrispondenza delle posizioni positive e negative sono stati utilizzati per addestrare il classificatore, il quale, ricevendo in input nuove immagini, può definire autonomamente la salienza dei punti sulla base dei loro descrittori e ottenere, così, un insieme di posizioni chiave. Questo procedimento richiede, però, l'estrazione dei descrittori in ogni punto dell'immagine e ciò comporta un alto carico computazionale. Questo, insieme allo stretto legame che vincola il metodo di descrizione utilizzato in fase di training a quello utilizzato durante il testing, limita la performance del detector. Per evitare queste problematiche, l'ultima parte del lavoro di tesi si è concentrato sulla creazione e addestramento di una rete neurale convoluzionale, utilizzando come esempi positivi piccole porzioni di immagine centrate nei punti in grado di fornire corrispondenze corrette tra diverse immagini. Si sono infine analizzate le performance dell'algoritmo sviluppato confrontandolo con lo stato dell'arte su un benchmark pubblico di riferimento.

ABSTRACT

State-of-the-art keypoint detection algorithms have been designed to extract specific structures from images and to achieve a high keypoint repeatability, which means that they should find the same points in images undergoing specific transformations. However, this criterion does not guarantee that the selected keypoints will be the optimal ones during the successive matching step. The approach that has been developed in this thesis work is aimed at extracting keypoints that maximize the matching performance according to a pre-selected image descriptor. In order to do that, a classifier has been trained on a set of “good” and “bad” descriptors extracted from training images that are affected by a set of pre-defined nuisances. First of all, the images used for the training have been sampled and matched by comparing the descriptor vectors obtained using a specific descriptor method. Then, the set of “good” keypoints is filled with those vectors that are related to the points that gave correct matches. On the contrary, randomly chosen points that are far away from the positives are labeled as “bad” keypoints. Finally, the descriptors computed at the “good” and “bad” locations form the set of features used to train the classifier that will judge each pixel of an unseen input image as a good or bad candidate for driving the extraction of a set of keypoints. This approach requires, though, the descriptors to be computed at every pixel of the image and this leads to a high computational effort. Moreover, if a certain descriptor extractor is used during the training step, it must be used also during the testing. In order to overcome these problems, the last part of this thesis has been focused on the creation and training of a convolutional neural network (CNN) that uses as positive samples the patches centered at those locations that give correct correspondences during the matching step. Eventually, the results and the performances of the developed algorithm have compared to the state-of-the-art using a public benchmark.

CHAPTER 1

INTRODUCTION

The paradigm of local features has been widely studied from the early 2000s and it is still matter of discussion among researchers all over the world. The most "interesting" points of an image, also known as keypoints, are the pivots of such paradigm that is based on three main steps: detection, description and matching. Finding corresponding points between images is a fundamental task for many applications, like object detection, SLAM (Simultaneous Localization And Mapping), augmented reality and many others.

The first step is the local features detection which searches across the images for points or shapes that are likely to be found in other images. In order to accomplish this requirement, it is necessary to define a priori what is the most distinctive characteristic that a group of pixels should deploy. For instance, the so called *"Canny Edge Detector"* [1] is one of the most popular algorithm when it comes to finding points between two image regions, whereas the method proposed by *Chris Harris* and *Mike Stephens* [2] relies on a function that gives negative values in case of edges, positive values for corners and zero for flat regions. Finally, algorithms exist that aim at the detection of regions of images that differ in properties. For instance, SIFT [3] (Scale Invariance Feature Detection) searches for the extrema of the Difference of Gaussian, i.e. the difference between several images obtained by applying a Gaussian filter with an increasing smoothing effect to the same initial image. The maximum is sought in space (8 pixels) and in scale (18 pixels).

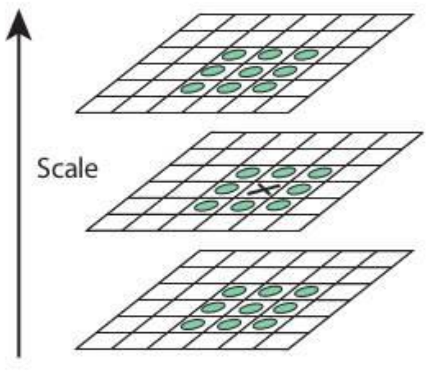


Figure 1-1. SIFT detector

Another example of feature detector is FAST [4] (Features from Accelerated Segment Test), where a point p is identified as keypoint if enough points on a circle centered at p all have a higher or a lower intensity with respect to the intensity of the central point.

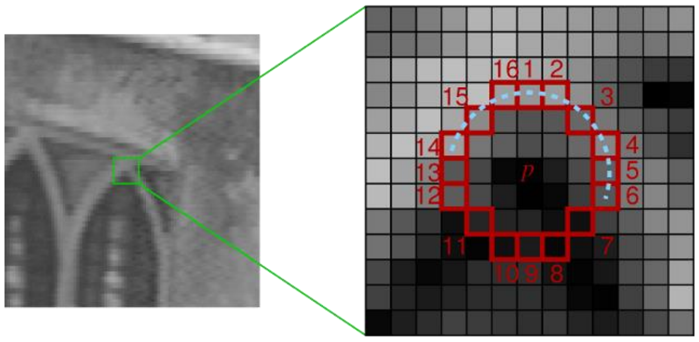


Figure 1-2. FAST detector

State-of-the-art keypoint detectors, such as the abovementioned ones, have been designed in order to achieve a high keypoint repeatability, which means that salient points have to be found in different views of the same scene despite possible transformations applied to the image, and in order to find specific shapes. For instance, *Canny* edge detector can find edges only, while *Harris* detector can identify both edges and corners. SIFT and FAST, instead, are specialized in both corners and blobs (regions).

After having detected the salient points over the images, they must be described so that it is easy to find them afterwards. This second step is aimed at creating a vector of numbers, by looking at the neighborhood of the point, in such a way that the result will have a high distinctiveness, i.e. it will capture the salient information around the keypoint, and a high compactness, namely low memory occupancy. Finally, as shown in **Figure 1-3**, corresponding points must be found in order to localize the salient point of the first image into the second one.

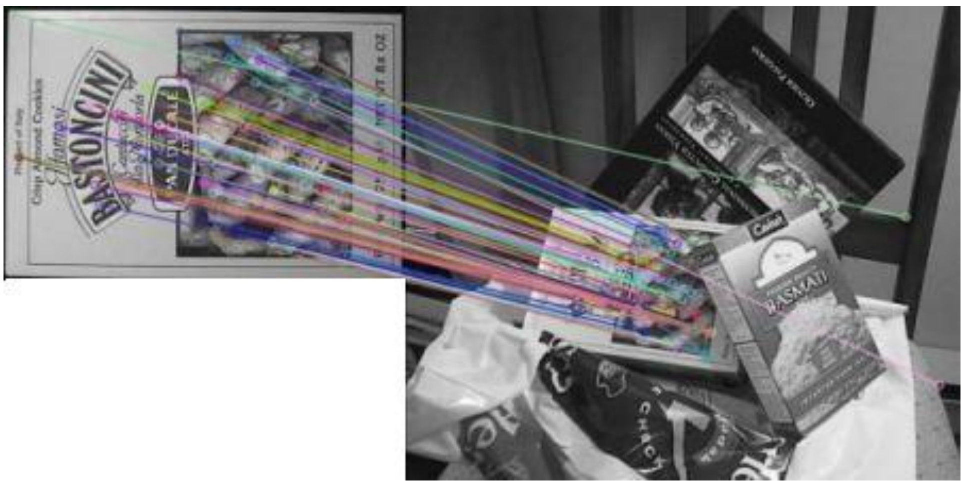


Figure 1-3. Description matching

Each element of the paradigm of local feature must work well itself; for instance, a measure of goodness for detectors is the repeatability, i.e. how many times the same point is detected over a sequence of different images of the same scene. However, the most important aspect is the whole detector-descriptor-matching pipeline output and this is only partially related to the repeatability of the detector. As previously mentioned, state-of-the-art keypoint detectors try to maximize the keypoint repeatability, but this does not guarantee that the points that have been found will be the optimal ones during the subsequent steps (description and matching). The idea behind this thesis is to create a keypoint detector that searches over input images for those points that will yield highly distinctive description vectors. In order to do that, a classifier has been trained so that it will judge each pixel of an unseen input image as a good or bad candidate for driving the extraction of a set of keypoints. This thesis work is a follow-up to a recently proposed paper titled *"Learning a Descriptor-specific 3D Keypoint Detector"* [9] that uses the same idea applied to the

3D case. As an alternative, in order to decouple the detector method from the choice of a specific keypoint descriptor, a convolutional neural network has been trained so that it is no longer necessary to define a priori the feature type.

The research approach of this work has been mainly developed using C++ and OpenCV along with already existing images datasets, namely some of the ones used as training set in *"Temporally Invariant Learned Detector"* (TILDE) [6], that is composed by images from the "*Archive of Many Outdoor Scenes"* (AMOS) [13] and panoramic images, in addition to the *"Oxford"* [14] and *"EF"* [15] datasets. For the last part, regarding the neural network modeling, Python and TensorFlow have been used.

The work is organized as follows: Chapter II describes the literature, in particular the paper TILDE, in which a classifier is trained using highly repeatable keypoints, and the paper *"Learning a Descriptor-specific 3D Keypoint Detector",* since these are the papers that are mostly related to this work; at the end of this chapter a brief explanation is also given about the two keypoint description methods used and some hints about how neural networks operate. Chapter III explains in detail the methods used in this work for the extraction of the positive and the negative samples, the training step and the testing procedure; Chapter IV shows the experimental setup and the qualitative and quantitative results obtained from the comparison between this method and the one proposed in TILDE; eventually, Chapter V gives some conclusions and an overview of the future work.

CHAPTER 2

LITERATURE REVIEW

The keypoint detectors that have been described in the introduction are all different and each one has its own specific algorithm; however, it is possible to split them in two main groups: the handcrafted keypoint detectors and the learned keypoint detectors. The former tries to overcome all the possible transformations an image can be subject to by looking for specific image structures, whereas the latter uses machine learning techniques to make the algorithm understand which are the most important features to be sought, starting from an initial input training set. For instance, SIFT [3] uses the *Difference of Gaussian* function as saliency function and it searches for the maxima of such function, while TILDE [6] and *"Learning a Descriptor-specific 3D Keypoint Detector"* [9] rely on previously trained classifiers for the keypoint detection. We will focus on these two papers.

2.1 Learning a Descriptor-specific 3D Keypoint Detector

The standard approach in 2D and 3D keypoint detection involves local saliency functions that give relevant locations at their maxima. However, this is not related to the quality of the descriptor that will be computed at those coordinates. In this work, it is proposed to train a classifier with points from a point cloud image that gives correct matches over a sequence of partially overlapping 2.5D views of the same 3D object.

2.1.1 Definition of the training set

The classifier that the authors want to train needs two separate sets: the positive sample set and

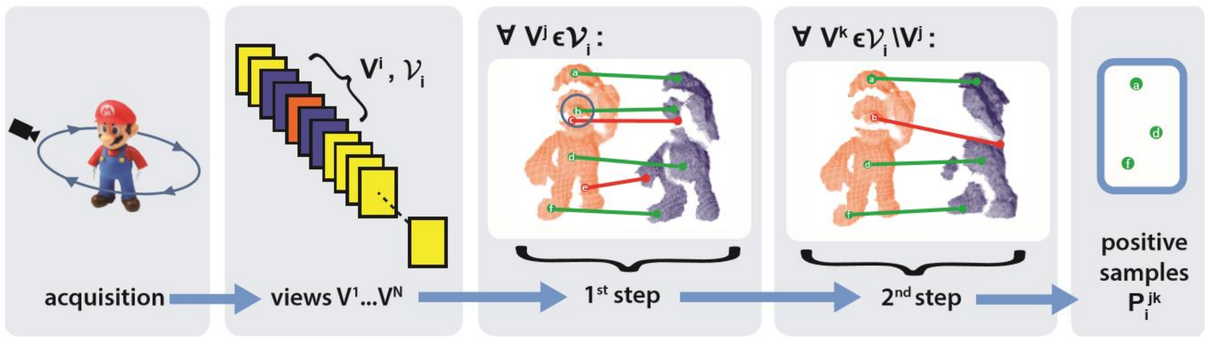

acquisition
$V^i, \mathcal{V}_i$
views V^1...V^N
$\forall V^j \epsilon \mathcal{V}_i$:
a
b
c
d
e
f
1st step
$\forall V^k \epsilon \mathcal{V}_i \backslash V^j$:
2nd step
positive samples P_i^{jk}

Figure 2-1. Overview of the definition of positive samples

the negative one. The extraction process of the positive sample points from the 3D image is shown in **Figure 2-1** and it is composed of five main steps. First of all, let *{V^i}* be the *N* partially overlapping views of the 3D object and let ν^i be the set of views partially overlapping with a view V^i. Then, in the third step, for every view V^i the SHOT [10] descriptor is computed at each point and the nearest neighbor SHOT descriptor in the overlapping view V^j is sought. Now the list of matched points is analyzed and if the match is correct the point is added to the list of positive samples, otherwise it is removed from the list. In the fourth step the list of positives is refined by checking if the positive samples can be robustly matched also in the other overlapping views. On the other hand, the set of negative points is randomly sampled from the set of points not included in the positive set.

2.1.2 Design of the classifier

The chosen classifier is a Random Forest [5], essentially because it is one of the fastest classifiers and, since it must be applied to every point of the point cloud, the speed is one of the most important elements to be considered. When using a classifier, a feature must be defined; usually, simple binary features such as intensity differences are used, but they need a local reference

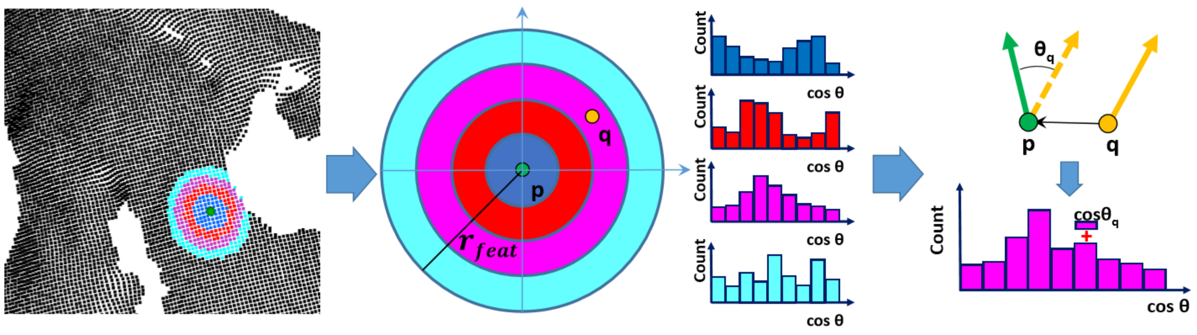


Figure 2-2. Feature extraction

frame to be defined, in order to preserve rotation invariance, and this increases the computational load. In this work, the authors store the cosine of the angle between the normal at the reference point p and the normal at every point within a radius r_{feat} in several histograms and use them as features. Since the histograms are computed for spherical shells, they are rotation invariant and then the local reference frame is no longer needed. Finally, when the classifier is applied to unseen input point clouds, the number of trees T_p that identify a point as a keypoint is counted and if the score T_p/T, where T is the total number of trees, is higher than a minimum score $s_{min} \geq 0.5$ and it is the highest value in a neighborhood of radius r_{nms}, then the keypoint is validated.

The procedure that has been used in this paper for the extraction of the positive samples is equal to the one used in this thesis work, except for the use of different invariant transformations. Indeed, in the 3D case, these transformations are 3D viewpoint changes, while in the 2D case, which is the one explored in this work, they are illumination changes.

2.2 Temporally Invariant Learned Detector

A great variety of keypoint detectors has been proposed since the 1980s and, even if they exhibit excellent repeatability with scale and viewpoint changes, they are all very sensitive with respect to illumination changes. In this work, the authors train a regressor using points that have been consistently found over a sequence of images that present drastic illumination changes due to different weather conditions.

2.2.1 Definition of the training set

The dataset that has been used for the training step is composed of two main groups:

- some images from the *"Archive of Many Outdoor Scenes"* (AMOS), that is a dataset that collects pictures from fixed webcams all over the world; the images are taken at different times of the day and different seasons;
- some panoramic images from a fixed camera located at the top of a building.

The authors trained the regressor on the images of one fixed webcam and then tested on the others along with further images from different datasets. After having collected a certain number

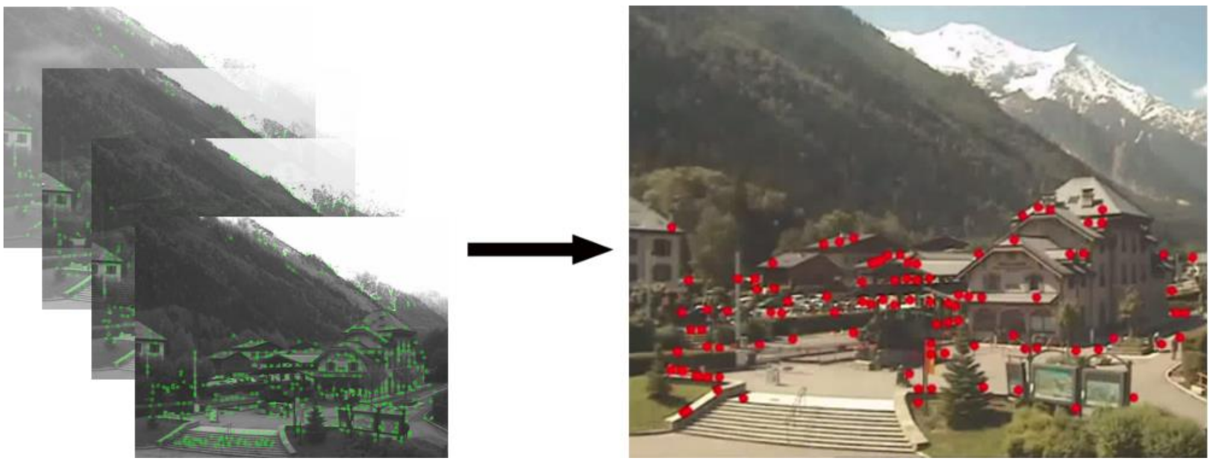


Figure 2-3. TILDE positives extraction

of images from one webcam, they applied SIFT detector to every image and they kept the 100 best repeated locations. Then, the set of positive samples is filled with the patches around these points even in the images where they have not been detected. The negative locations, instead, are just points far enough from the keypoints used to create the set of positive samples.

2.2.2 Design of the regressor

The features that the authors of the paper used are the three components of the LUV color space, the vertical and horizontal gradients and the gradient magnitude computed at each pixel of the patches. Since the detector will be applied to each location of the images, the speed of the algorithm is a crucial element. Thus, here a fast regressor is used, that applies only simple convolutions and pixel-wise maximum operators:

$$F(x;\omega) = \sum_{n=1}^{N} \delta_n \max_{m=1}^{M} w_{nm}^T x \ , \tag{2-1}$$

where x is a vector of image features extracted from the patches, ω is the vector of parameters of the regressor and it can be decomposed in a combination of linear filters w_{nm} and a set of parameters δ_n. The linear filters are the elements to be learned through an optimization function over the training images and they can be approximated as a linear combination of separable filters. At the end two different methods can be used: TILDE-P, that uses the original filters and TILDE-P24 that uses 24 separable filter in order to speed up the process.

As already mentioned, TILDE is probably the most related to this thesis work in the sense that the authors used a machine learning technique to learn a 2D keypoint detector starting from a set of positive and negative samples. As a consequence, the datasets used in this work for the training and testing steps are the same.

2.3 BRIEF and FREAK Descriptors

"Binary Robust Independent Elementary Features" [7] is a description method that, when applied to a certain image patch around a point of interest, returns a binary descriptor, where binary means that is composed by 0s and 1s only. When we want to find correspondences among points of more images, the comparison between such type of descriptors can be very convenient with respect to non-binary vectors, because it allows the use of the Hamming distance and, then, a considerable speed-up of the matching step. SIFT descriptor would require a conversion from the standard vector to the binary equivalent if the Hamming distance is being used, whereas BRIEF extracts a binary value directly from the patch itself. Indeed, the idea behind BRIEF is to pick random points from a Gaussian distribution and test them. The Gaussian distribution has the following form:

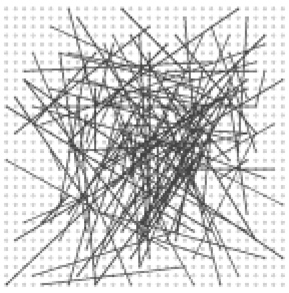


Figure 2-4. BRIEF pairs

$$(x,y) \sim i.i.d\ Gaussian\ (0, \frac{1}{2*S} * S^2) \ , \tag{2-2}$$

where S is the patch size. The test gives as result 1 if the intensity of the pixel x is lower with respect to the intensity of y and 0 otherwise. If we proceed through many pairs we will end with a string of binary values that is the BRIEF Descriptor.

This type of descriptor, tough, is very sensitive to rotation; indeed, if the image is rotated by more than a few degrees, the matching performances of BRIEF falls off sharply. Randomly picking up points from a Gaussian distribution is not the only possible choice to select the locations that are processed by the test. The authors of the work *"Fast REtinA Keypoint"* [4] tried to understand which are the best pairs to be used for the test by analyzing the human visual system. **Figure 2-5** shows the comparison between the points used for the test along with their Gaussian blur radius and a human retina region responsible for sharp central vision that is composed by three main elements: fovea, parafovea and perifovea. Similarly to what happens in our eyes, the outer points (perifoveal area) are the first to be analyzed because they are the most discriminative locations, while the central points (foveal area), that are the least blurred ones, are the last pairs to be tested.

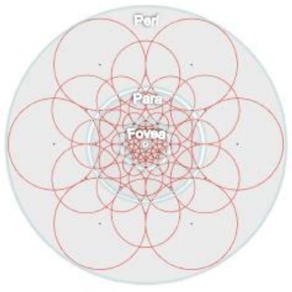


Figure 2-5. FREAK test points

Regarding rotation invariance, the orientation is estimated by summing the local gradients of some pairs that are symmetric with respect to the center of the patch.

2.4 Neural networks

Neural networks are one of the most used machine learning techniques that have become very popular in the last few years thanks to the decrease of hardware prices and to more performant GPUs (Graphic Processing Units) for personal use. Neural networks with different architectures are used for countless applications, like speech recognition, understanding of biological data, character text generation and many others. Concerning the computer vision field, deep learning, i.e. the branch of machine learning that uses neural networks, is widely used for object classification, colorization of black and white images, medical images segmentation and so on.

The human visual system can perform extremely complex image analysis. This ability is the consequence of millions of neurons linked by billions of connections inside the five visual cortices of our brain. Our efficiency in visual pattern recognition is the result of a long training process that last many years and that teaches us how to perfectly use our powerful eyes. As a consequence, it is not so easy to imitate the human visual system in all its complexity and to carry out a proper training procedure. **Figure 2.6**, which shows some handwritten digits from the MNIST (Mixed National

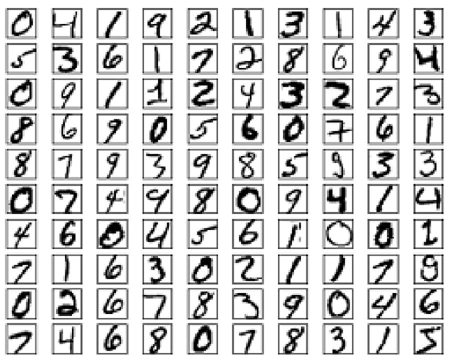


Figure 2-6. Some digits from MNIST

Institute of Standards and Technology) dataset, is an example of how easy is for the human brain to recognize such images as meaningful information. If we want to create a computer program capable of understanding which number is in front of a camera, though, it would not be easy at all. For instance, we could try to identify the digit "1" by assuming that a fundamental characteristic is the bar at the bottom of the stroke. The problem would be that with such a precise rule it can be hard to identify other "ones" that deploy different features and if we start adding exceptions we could end up in many wrong classifications. Therefore, we need something more powerful and, at the same time, flexible with respect to small variations.

2.4.1 Artificial neural networks

Artificial neural networks (ANNs) are a machine learning technique that can infer specific characteristics of an input training sample and then seek them during the testing step. When we use this algorithm, we do not need to define a priori which shapes identify a sample as belonging to a certain class; indeed, it is the network itself that will learn how the elements of the training data associated with a label must be distributed. For instance, in the case of handwritten digit classification, the feature to be learned is the distribution of pixel intensities over the images.

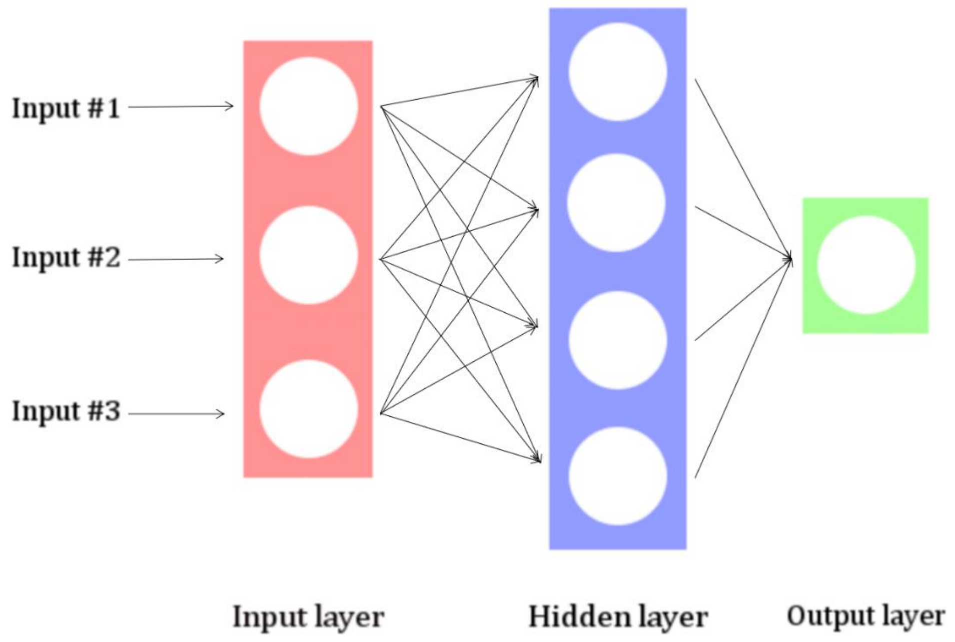


Figure 2-7. Simple neural network architecture

ANNs are inspired by and loosely based on biological neural networks. Indeed, the idea behind the functioning of ANNs is to use many linked elementary units in order to achieve high performances when dealing with complex tasks. All these interconnected neurons exchange information and update every time a new training sample is injected along with its label. In practice, the neural network should learn a set of weights and biases that, when combined with the input will give us back a probable prediction of a certain label as output. For instance, if our input is *x* we must initialize the set of weights and biases and then, using the formula

$$\hat{y} = W * x + b \tag{2-3}$$

we compute the predicted output and we compare it to the real value of y, that we know since all the training data come with their own labels. The aim of this procedure is to minimize a cost function time by time, by updating weights and biases at every step of the training. This optimization problem can be solved in several ways, for example using gradient descent, stochastic gradient descent and some others. The output of every node is the result of a linear process and, even if its efficiency is high, especially using GPUs and simple matrix operations, a non-linear component is necessary, otherwise the network would lose the ability to model non-linear patterns. Therefore, the output of the linear equation (2-3) is processed by the so-called activation function. **Figure 2.8** shows an example of activation function called ReLU (Rectified Linear Unit) that gives *y=0* if x is negative and *y=x* if *x* is positive. The advantages of this function are that it is differentiable everywhere except in zero and its derivative is very simple: zero if *x* is negative and 1 if *x* is positive.

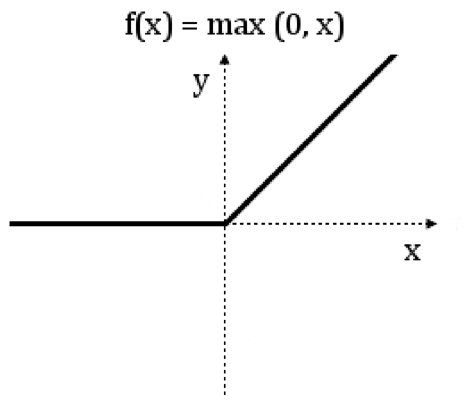


Figure 2-8. ReLU

A simple ANN (for example with only 2 layers) can approximate a large variety of models but it uses many nodes and it needs many training images in order to get acceptable values for every parameter. A good solution to these problems is to increase the depth of a network by adding many layers and to reduce the number of nodes per layer.

2.4.2 Deep neural networks

A deep neural network is a very powerful tool that uses many layers of abstraction to infer features of some input signals. The structure of such network is composed by several layers one on top of the other in a way that every layer tries to elaborate the outputs of the previous layer in order to get the best possible prediction for the output. When using deep network, the number of inputs used for the training procedure can be lower with respect to the simple ANNs, and this can easily lead to overfitting, namely the problem of having a too complex model that can hardly work in a general case. In order to solve this problem, it is used the so-called regularization and a possible technique that has been recently proposed is called dropout. The idea behind this technique is to deactivate 50% of the nodes during each iteration of the training step such that the algorithm can never rely on the same inputs.

Deep neural networks, like ANNs, can be developed using many possible architectures that change depending on the depth of the network and on the type of layers used. When dealing with images, a widely used types of layers are convolutional layers and pooling layers, that can be combined together in order to analyze the spatial information of an image. The main reason it is possible to use this approach with images is that pixels can share their weights to reduce the degrees of freedom of the model.

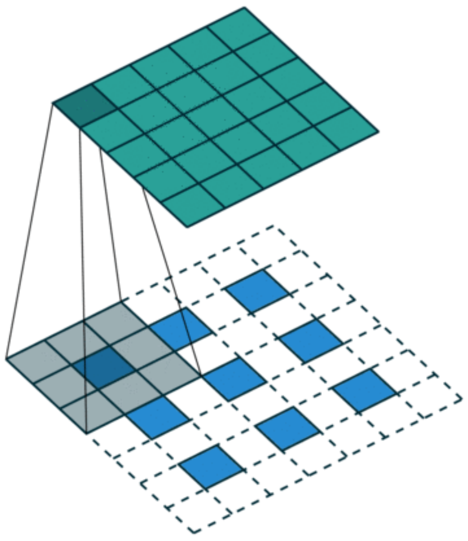


Figure 2-9. Convolution

A convolutional layer is a layer in which a simple square filter is applied as a sliding window over the images. The main parameters here are the dimension of the filter, the stride to use, i.e. how many pixels must be skipped between two filters and whether the size of the image after the convolution should remain constant or not. When applying convolutions on the borders of an image, some pixels could be missing since the filter is only partially overlaid to the image. In this case, we have two possibilities:

- use some padding (for instance zero-padding) in order to get some information also on the edges of the images;
- apply the convolution without any padding and skip all the locations where the filter could not be computed. In this case the dimension of the images will not remain constant.

The output of this layer will be, then, an image with the same dimension (if padding is present) and a certain depth that indicates the number of channels. **Figure 2.9** shows an example of convolution with a stride of 1 along all the directions. In this case the padding is not used, thus, the final image has a smaller dimension, more specifically, one pixel is “lost” on one boundary and one on the other boundary.

Another type of layer is the pooling layer that is used to reduce the spatial dimension but it keeps the same number of channel of the input image. The downsampling is carried out by taking some information from a cluster of pixels using a specific criterion. For instance, **Figure 2.10** shows the so-called max pooling layer, that takes the maximum intensity among the ones of the pixels within a sliding window. The parameters to be set here are the size of such sliding window and the strides.

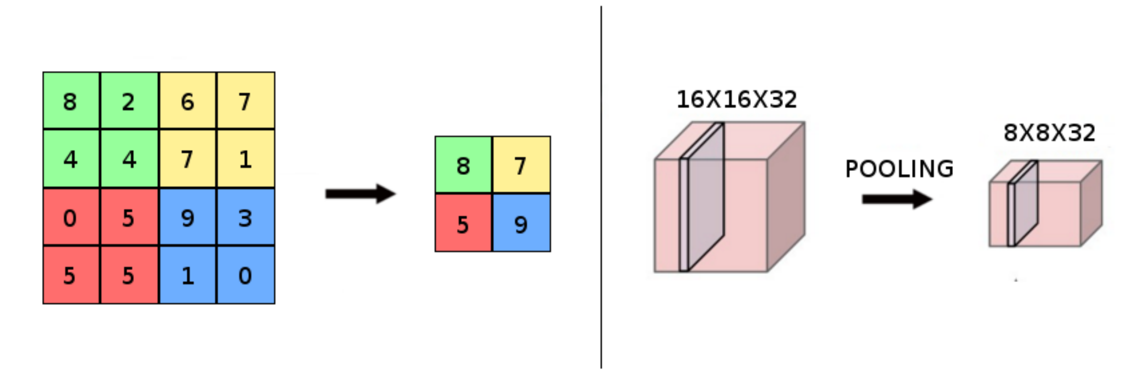


Figure 2-10. Max pooling

As already mentioned before, many architectures can be implemented by changing the parameters of the layers and the number of layers itself. **Figure 2.11** shows the so-called "LeNet" architecture, created in 1998 by Yann LeCun for handwritten letters recognition.

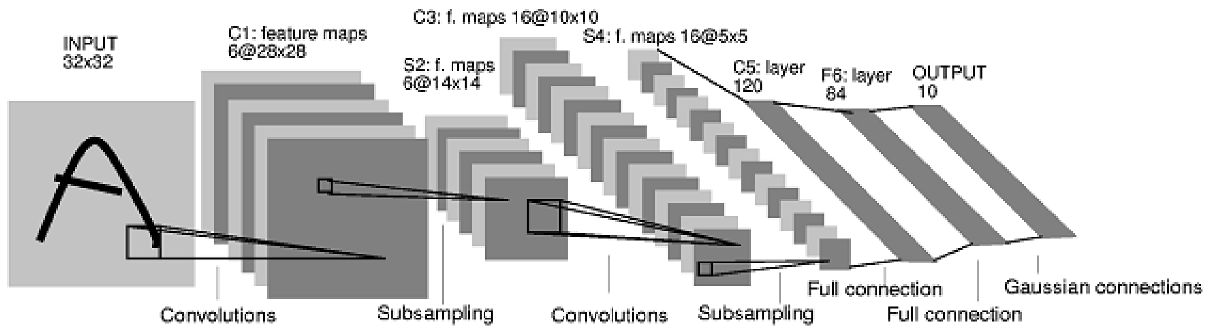


Figure 2-11. LeNet architecture

CHAPTER 3
METHODS

3.1 Samples extraction and training of the classifier

The procedure that has been used in this thesis is the same as in the previously mentioned *"Learning a Descriptor-specific 3D Keypoint Detector"*; indeed, the set of positive samples has been extracted from those points that gave a good correspondence during the matching between images of the same scene affected by specific transformations. In the 3D case, these transformations were 3D viewpoint changes, while here the viewpoint is always the same, but the images have acquired under different lighting conditions. Since this work is aimed at learning features from 2D images, the most relevant comparison that can be performed is with TILDE and, in order to make an even comparison, the dataset used here is the same of the one used in TILDE, for both training and testing. As already mentioned, the training dataset is composed by some images from the *"Archive of Many Outdoor Scenes"* (AMOS) dataset and panoramic images collected by the authors of TILDE, while the testing dataset is composed again by some images from AMOS and panorama.

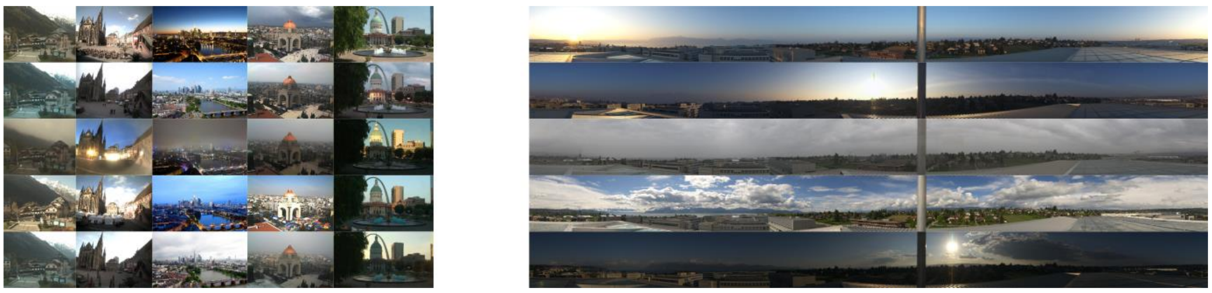

(a) (b)

Figure 3-1. Images from AMOS (a) and Panorama (b) datasets

The whole procedure is developed through many small steps and each one of them needs specific parameters to be tuned. First of all, all the images of the training dataset are sampled and a descriptor is computed at every location; then, a matching step is performed and a table containing information about how many times a point has given a correct match is created; finally, the points are sorted from the ones with the highest goodness score down and the best ones are kept as positive sample locations. The set of negative samples is randomly sampled over the images in such a way that every point is far enough from both the already computed positives and the other negatives. In one of the two approaches used in this work, the features that will be used during the training of the classifier are vectors of description computed at the positive and negative locations of every image of the training dataset, that are stored into vectors and will be used later. In the other case, with CNNs, it is not necessary to determine a priori the features that we need to feed because the neural network can learn these features autonomously, therefore the only thing we need from the locations detected by the matching procedure is the distribution of the intensities around them. **Table 3-1** shows all the possible parameters that are combined and compared in order to determine which is the best arrangement to be used for the first step of this keypoint detector. The extraction of positive and negative samples is, of course, used in both random forest approach and CNN approach. The comparison will take place during the validation step and it will involve also other settings related to the classifier. In the next sections, the steps for the positive and negative samples extraction are explained in detail.

Table 3-1 List of the parameters

SAMPLING RATE	3	5	8
DESCRIPTOR TYPE	BRIEF	FREAK	
MATCHING TYPE	STRAIGHT	CROSS	CROSS-RANDOM

3.1.1 Sampling and description

The first important step is the training images sampling. Indeed, we need a set of points that will be compared to the others belonging to the remaining images of the dataset. Even if the sample extraction and the training of the classifier are both offline processes, meaning that they can be computed before the application of the keypoint detector to the test images, the speed of the whole process is important in practice. On the other hand, if we speed up the process by applying

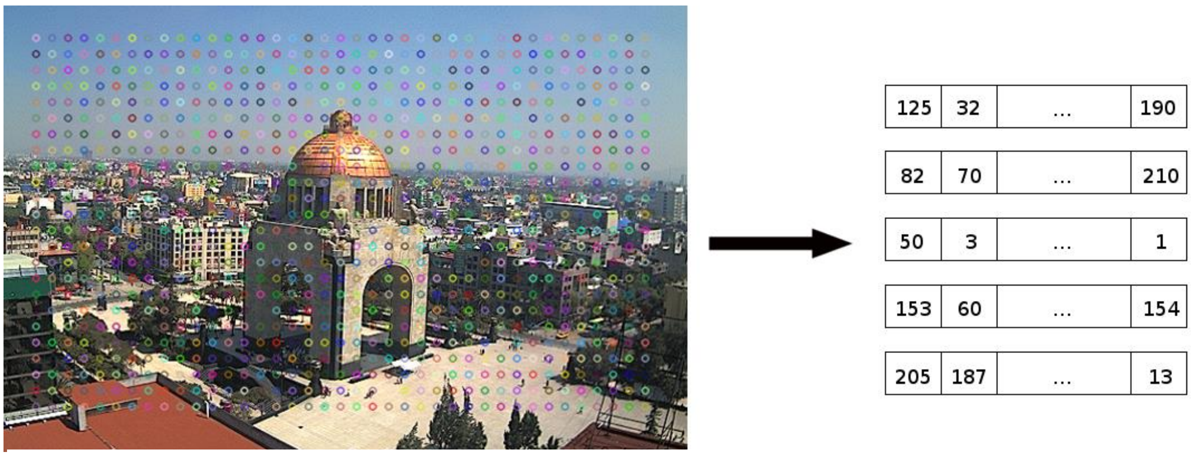


Figure 3-2. Image sampling and computation of the descriptors

a very low sampling rate, many points would be discarded and the number of positive candidates would be too low. To sum up, a dense sampling would be better in terms of quality of the positive samples, but very slow, while a high sampling rate would make the process fast but not very precise.

The main parameters to be set here are two:

- the sampling rate of the input images;
- the descriptor to be used.

For the latter, while both detector and descriptor are included in the SIFT procedure, descriptor methods like *"Binary Robust Independent Elementary Features"* (BRIEF) [7] and *"Fast REtinA Keypoint"* (FREAK) [8] do not have an already integrated detector. The choice of the description method in this step must be the same during the final testing step when using the random forest, because if we train a classifier to recognize a specific pattern that is related to a certain descriptor type it will not recognize vectors created in a different way. It is possible to note in **Figure 3.2** that many points on the borders are missing; the reason is that when the descriptor vectors are created, as already mentioned in Chapter 2, the intensities of many points around the central one (in this case the sampled point) are compared by looking at their intensities and if one or both points happen to be outside the image a problem occurs. In this case the point of interest is skipped and it is removed by the set of keypoints, but this aspect strongly depends on the choice of the description method.

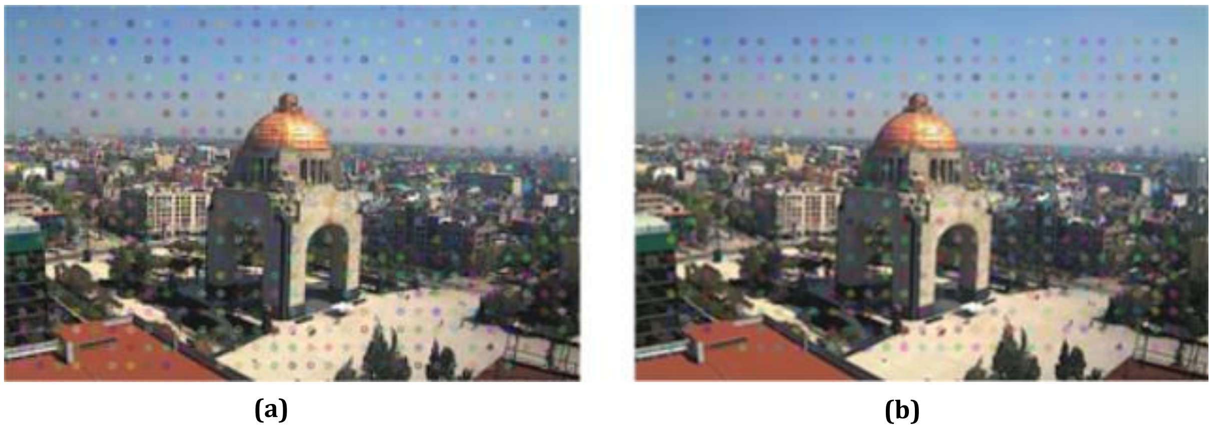
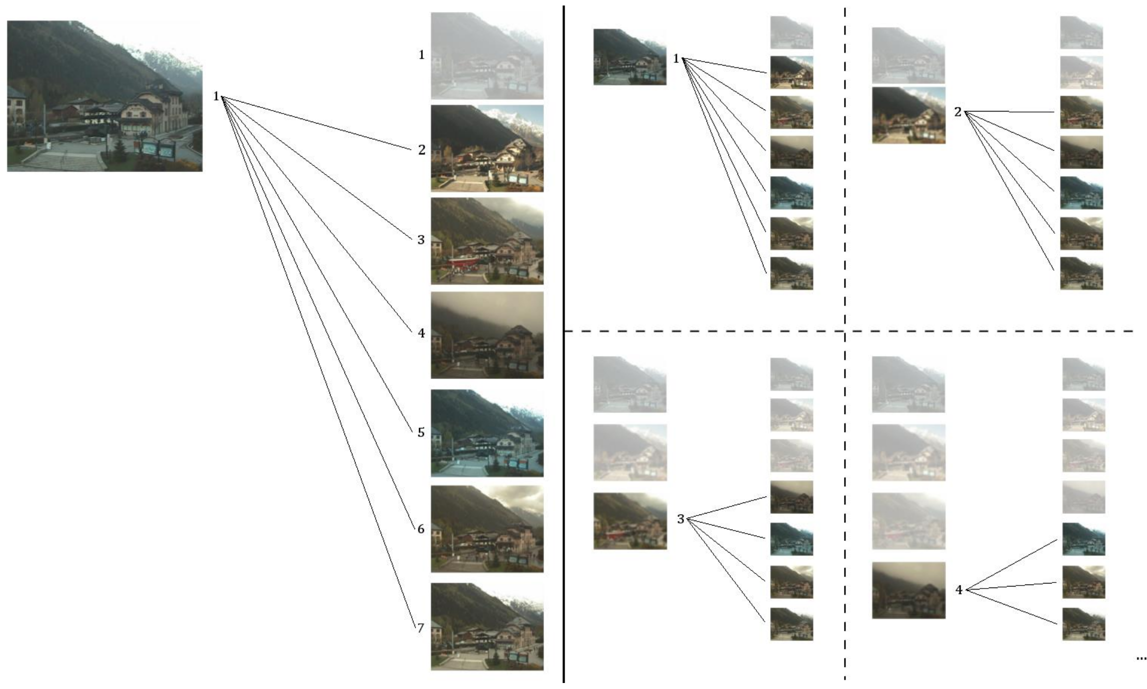

(a) **(b)**

Figure 3-3. Keypoints removal: (a) before the computation of the descriptors, (b) after

In the case of CNNs, the problem of computing vectors of description before the testing procedure is not important since the features are inferred directly by the network. However, this first step has two purposes: the localization of the points that should be good for the training procedure and the extraction of the descriptors that will be used later when training the random forest. The former aim is common to both the random forest and the CNN and it needs anyway the computation of the descriptors in order to perform the matching procedure; thus, the problem of missing keypoints near to the boundaries cannot be avoided. The CNN, though, deals with patches and, even if there are no intensity differences, it could be possible that a portion of some patches covers an area that exceeds the boundaries of the image. Since we are discarding some points that are far enough from the borders, it will be always possible to extract all the patches centered at those points.

3.1.2 Matching

The second step is the matching, in which all the descriptors of two images are compared in order to find the best correspondences. This is the main difference with respect to TILDE, because, while TILDE extracts the best locations by applying an already existing keypoint detector and it labels a point as positive if it can be consistently found over the sequence of images, here a point is good only if it gives many times a good correspondence. In this specific case, since all the training images are already aligned, a good correspondence means that a point on the first image of a compared pair must point to a location in the second image of the pair with exactly the same coordinates. If it was not the case and similarity transformations were applied, a perspective matrix would have been needed in order to find the correct position.



(a) (b)

Figure 3-4. Matching types: straight matching (a) and cross matching (b)

The procedure to follow in order to find the positive locations can be various and the main parameter to decide here is which images will be compared. As already mentioned before, the used dataset is the same of TILDE, in which 100 images from the same webcam form the training set. Of course, the best solution would be to perform a cross matching between all the possible pairs of a training dataset, but it would require a lot of time. A workaround to this problem is to perform the matching step only over a subset of images from the training set and then extract the descriptors from the whole set, but this forces us to choose the images to use. This decision is very important since a wrong choice of the images could lead to favor specific features. For

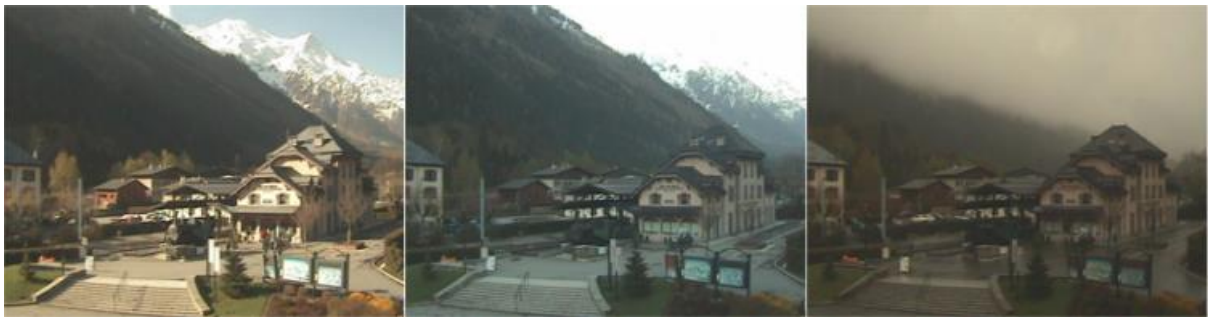


Figure 3-5. Some images from the Chamonix training dataset

instance, **Figure 3.5** shows a comparison between 3 different images of the same scene under different illumination and weather conditions. It is easy to note that if images with the same illumination and weather of the third image are not present among the images that must be compared, some points of the mountains in the background could be detected as positive and the final result could be biased. On the other hand, checking all the images and trying to manually hardcode the dataset could be very time wasting. A possible solution, then, is to inject randomness and let it decide for us. In this work three possibilities have been developed:

- a match between the descriptors of the first image of the dataset and all the others (straight approach);
- a match between pairs of images from a subset of the dataset composed by the first 30 images of the dataset (cross approach);
- a match between every image of the dataset and a subset of the dataset (cross-random approach).

In the first case the number of combinations is obviously smaller; indeed, if N is the number of images inside the dataset, N-1 matchings will be necessary, while in the cross matching case the procedure must be executed $\frac{N!}{k!(N-k)!}$ times, where k is 2 since every comparison is between 2 images only. In order to keep the sample extraction time almost constant, N must vary depending on the matching type we want to use. In the "straight" matching, 100 images have been used, exactly like TILDE, whereas, in the cross matching, 15 and 30 images have been used, resulting in 105 and 435 comparisons respectively. In the last case, every image of the training set is compared to some randomly chosen images, thus the number of comparisons depends on the times a random number, associated to an image, is chosen. A possible negative drawback here is that randomly choosing a number does not guarantee that images like the third one of **Figure 3-5** are chosen and this can affect the final positions of the positive samples. The main parameter to be set here is the descriptor type, that can be either BRIEF or FREAK, but also the matching algorithm is important; indeed, once the descriptors have been extracted around the points, the way in which they are compared can affect the final result. The tested alternatives are the Brute-Force Matcher, that takes the descriptor of one feature and compares it to all the others, and two matchers from the *"Fast Library for Approximate Nearest Neighbors"* [11] that use KDTree and Locality Sensitive Hashing. These two last methods are very fast in case of large dataset and for high dimensional features, but, since this is not the case, they are slower with respect to Brute-Force Matcher.

The objective of this matching step is to fill a table with information about the "goodness" of every point in terms of matchability. This table is initialized as shown in **Table 3-2**, where *X* and *Y* are

Table 3-2. Score table initialization

X	Y	ID	SCORE
0	0	1	0
0	Sampling rate	2	0
…	…	…	…
Max width	Max height	Max ID	0

the coordinates of the sampled points, ID is necessary to identify every keypoint and the score is a value that indicates how many times a point has given a correct match over the sequence of images. When the first descriptor matching is executed, every point of the list of matches is checked and if the corresponding point given by the matching algorithm is in the correct position, where correct means in the same position of the first point of the pair, then the location coordinates are stored in a vector. It is important to note that a small matching error (1 or 2 pixels) is accepted and then a point gives a correct correspondence even if it is not exactly at the right position.

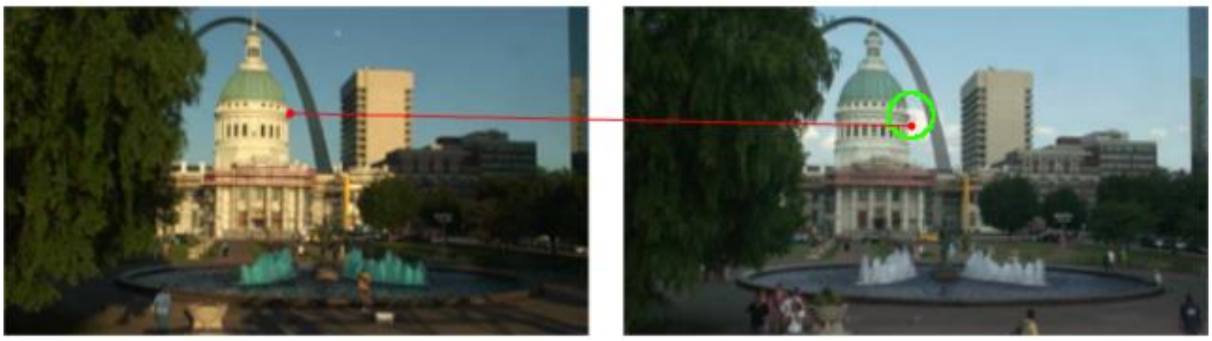
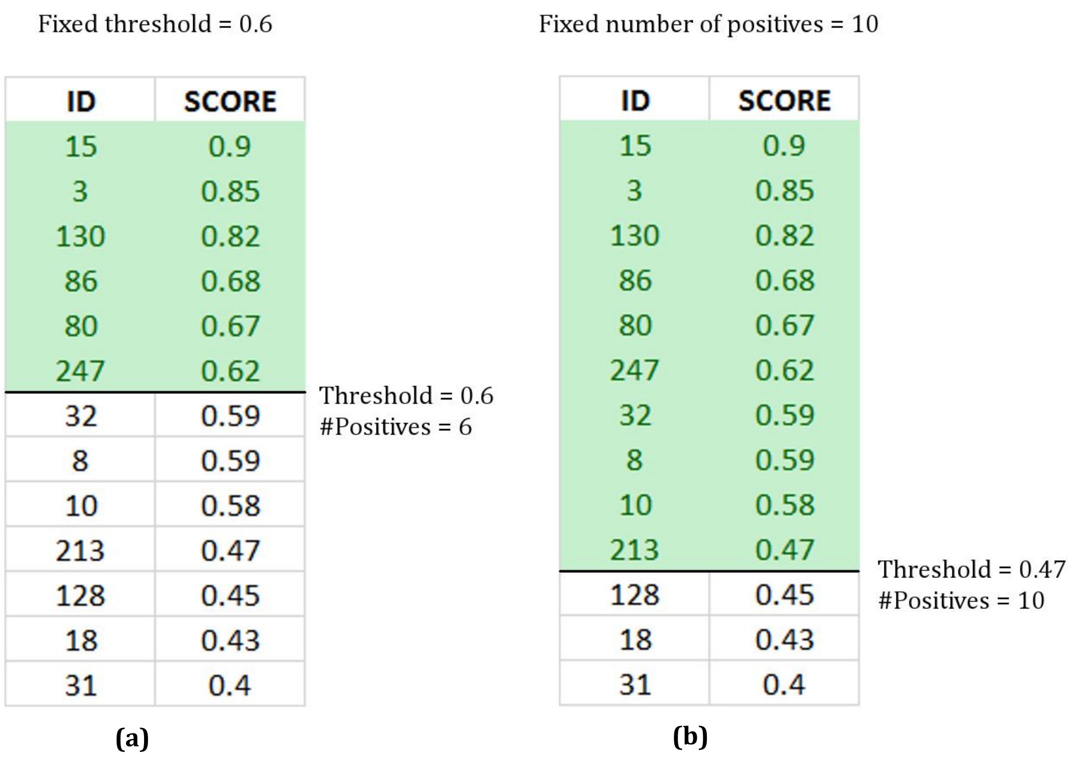


Figure 3-6. Matching error

At the end of this step, every positive location of the vector is sought over the score table and its score is increased by $\frac{1}{Total\ number\ of\ comparisons}$ that, in the case of straight matching, is equal to $\frac{1}{N-1}$, where N is the number of images, while in the case of cross matching is $\frac{2}{N(N-1)}$ since the number of comparisons is $\frac{N!}{2(N-2)!}$. The last case, namely the cross-random approach, is slightly different because the score of a positive point is increased by $\frac{1}{N*imgsToCompare}$, where *imgsToCompare* is how many random numbers are extracted for every image. When a point gives a correct correspondence, its location is updated and, as already mentioned before, no similarity transformation is needed since the training set is already aligned.

3.1.3 Positive and negative sample extraction

At this point, every location of the image has its own score that tells us how good the descriptor is, around those points to be matched later. In order to choose the best points, we have two possibilities: set a threshold on the scores and take all the points above that threshold or sort out all the points of the table from the one with the highest score and use a dynamic threshold that,



Fixed threshold = 0.6

ID	SCORE
15	0.9
3	0.85
130	0.82
86	0.68
80	0.67
247	0.62
32	0.59
8	0.59
10	0.58
213	0.47
128	0.45
18	0.43
31	0.4

Threshold = 0.6
#Positives = 6

(a)

Fixed number of positives = 10

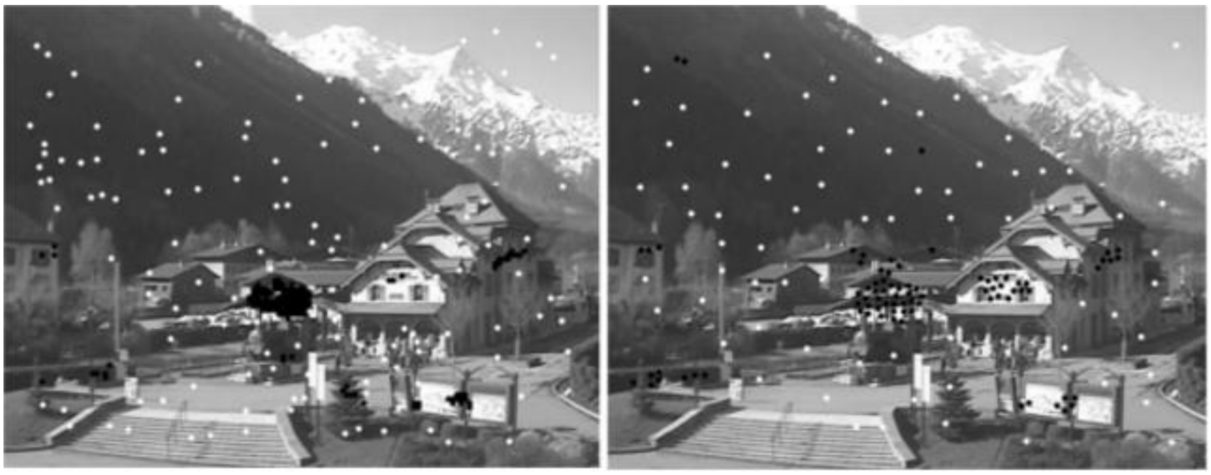
ID	SCORE
15	0.9
3	0.85
130	0.82
86	0.68
80	0.67
247	0.62
32	0.59
8	0.59
10	0.58
213	0.47
128	0.45
18	0.43
31	0.4

Threshold = 0.47
#Positives = 10

(b)

Figure 3-7. Fixed threshold (a) and dynamic threshold (b)

starting from 1, keeps decreasing until the number of points with a score higher than the threshold is greater than a predefined value. In the first case, when we set the threshold to a certain value, for instance 0.6, we do not know how many points will be found later and this can be very bad because we could get either too many or too few points. For example, if a sequence of images is not affected by strong transformations, all the sampled points of the images can get a very high score and, with a low threshold, they could be all labeled as positive samples and during the testing step this results in a very low selective keypoint detector. Moreover, if the positive samples distribution is too dense, when the negative samples will have to be randomly picked, it will be hard to find points that are far enough from the good sample locations. On the other hand, if the dynamic threshold is used, the minimum number of positive samples that we want must be chosen beforehand, but the threshold changes and decreases as long as enough points are selected. This could result in a set of positive samples with a very low score that will have a bad influence on the final classifier. In this work, the dynamic threshold approach is used during the positive extraction procedure and the afore-mentioned problem does not exist anymore since the images suffer from illumination changes and not from similarity transformations, which means that many points can get a high score. Later in the process, during the testing step with random forests, will be necessary to decide which approach to use between the fixed and the dynamic threshold, and the best solution will be a fixed threshold since it is possible to adjust it before the real use of the algorithm.



(a) **(b)**

Figure 3-8. Positive (black) and negative (white) locations: (a) Sampling rate = 5. (b) Sampling rate = 3, with non-maxima suppression

The sampling rate defined during the first step of the process, when the images are sampled, could discard many points that could get a high matching score during the second step. As already mentioned, the best solution would be to analyze every pixel so to be sure that no good locations are left behind. However, this approach would require a lot of time and moreover, the OpenCV library, used in this thesis, does not allow to fill the set of training descriptors with more than 262144 items, limit that is easily reached by images like the one in **Figure 3-8**. Another important problem associated with the dense sampling is that many points of the same area can be detected as positive and this can lead the process to an extraction of many descriptors (in case of random forests) or patches (in case of CNNs) that are too similar.

Having a large variety of training data is fundamental for a good estimation because, otherwise, the algorithm cannot learn enough features and its predictions are not precise. In order to spread the points and cover a wider surface, the points are sorted from the one with the highest matching score to the one with the lowest. Then, starting from the first point, the locations around its coordinates within a certain radius are checked and, if their scores are lower with respect to the central one, they are discarded from the list of positives. **Figure 3-8 (a)** shows an example of positive samples extraction with a sampling rate of 5 pixels without any improvement, while **Figure 3-8 (b)** shows a training image with a sampling rate of 3 pixels and the previously explained technique with a radius of suppression equal to 6 pixels. Since the sampling rate is 3 pixels, having a radius of suppression equal to 6, 7 or 8 pixels does not make difference, because it is not possible to find a sampled pixel between the 6th and the 8th pixels.

3.1.4 Features extraction

When the final set of positive locations is complete, the features set that will be used for the random forest training is formed by all the descriptors computed at the positive locations over

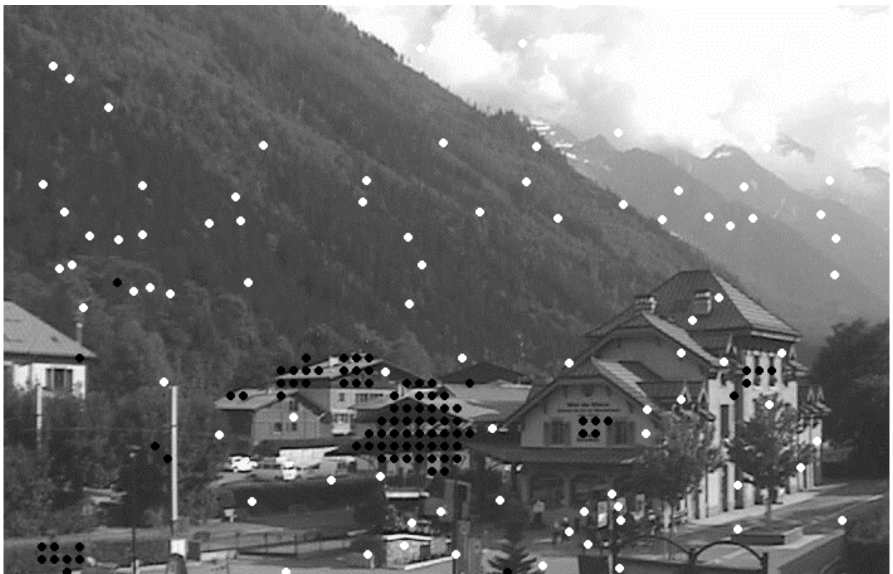


Figure 3-9. Example of positive (black) and negative (white) locations with sampling rate = 10 and negative radius = 10

every image of the training dataset, even in those where a certain location did not give a correct match during the previous step. Regarding the CNN, instead of the descriptors set, a set of patches extracted from the area around the selected positive and negative points is used.

The negative locations are randomly picked from the images in such a way that they are far enough from every positive location and every negative location. Basically, a pair of integers are randomly sampled within a range defined by the width and the height of the images of the dataset; then, they are compared to the coordinates of the positive samples and if they are far enough from every positive location they are labeled as non-positive locations. In order to have a large variety of negative samples, the non-positive coordinates are also compared to all the points that are already inside the negative samples set and if the distance is greater than a certain value they can be inserted into the negative samples set. **Figure 3-9** shows an example where the sampling rate is 10 pixels and the negatives (white dots) must have at least a distance of 10 pixels from both the positive and negative locations. In this thesis work the negative radius will be equal to 30 pixels. Using the random forest trained with the descriptors computed at the positive and negative locations is more efficient with respect to the CNN, because all the descriptors we need are already available from the sample extraction. When applying the CNN, instead, all the patches centered at the positive and negative points must be extracted and used for the training of the network.

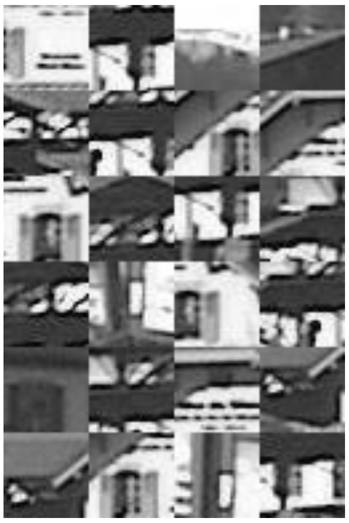


Figure 3-10. Some of the 32x32 patches used to train the CNN

3.1.5 Training of the random forest

The last step is the training of the machine learning algorithm. For this work, the chosen classifiers are the random forest, similarly to what has been done in “Learning a Descriptor-

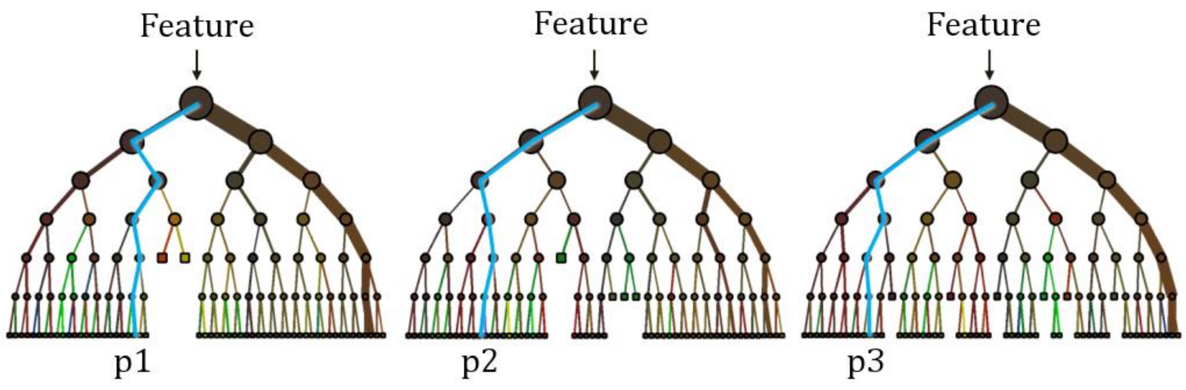


Figure 3-11. Random Forest structure

specific 3D Keypoint Detector" and a convolutional neural network. A Random Forest is a cluster of decisional trees that, given an input sample, tries to predict which class the input belongs to by computing the means of all the results coming from each tree. The word "random" means that the initial dataset is randomly split in many overlapping subsets and the same is done to the "questions" to be asked at every node. When the classifier is trained, a bunch of labelled elements (in this case the labels are "positive sample" and "negative sample") is given to the algorithm that decides which are the best question to be asked in order to get the best split of the input data. The parameters to be tuned here are two: the number of trees to be used inside the forest and the depth of every tree, which is measured in terms of how many times we want the classifier to split the input data into smaller subsets or how many samples we want to be left at a node. Having a

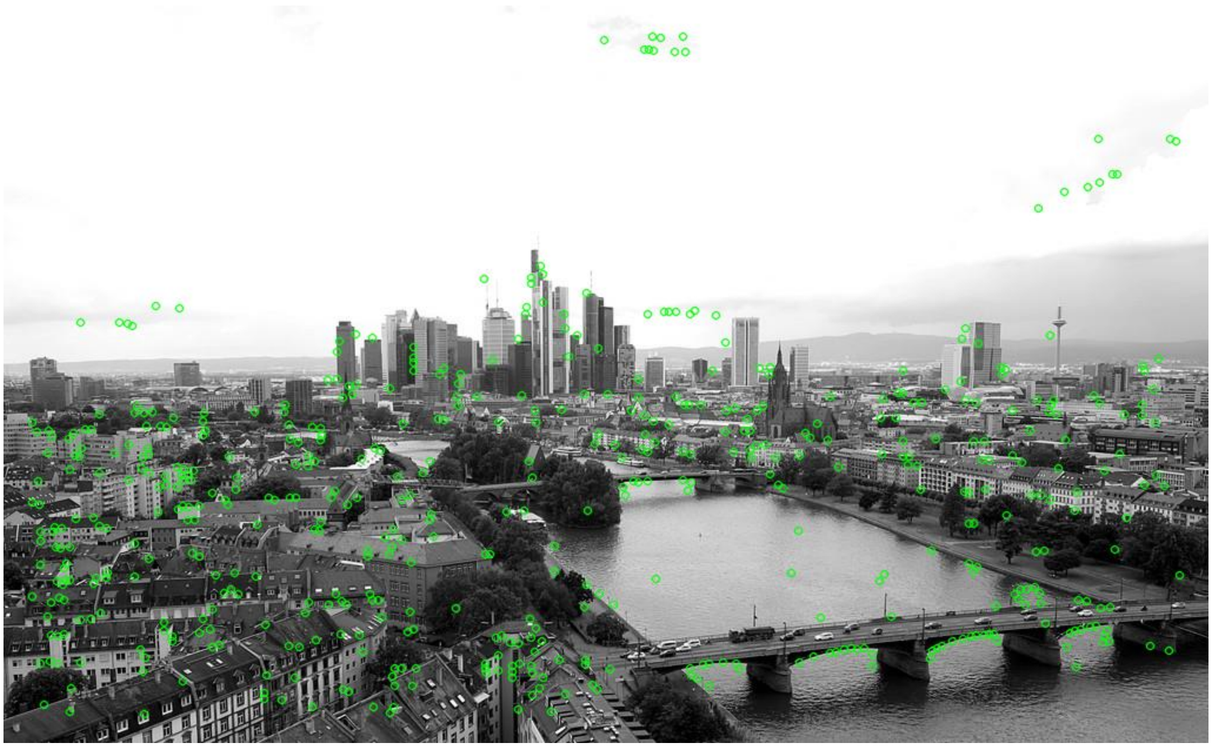


Figure 3-12. Example of problems with clouds: Frankfurt webcam using a random forest trained on Chamonix dataset

high number of trees and a high depth can be better in terms of quality but worse in terms of speed, thus a good trade-off should be found. When the classifier is trained, the algorithm asks a sequence of questions to every feature we put inside of it and it gives back the probability associated to a final leaf. In this thesis work, the features used for the training of the classifier are the description vectors obtained at certain locations using either the BRIEF descriptor and the FREAK descriptor. Using a descriptor to train a classifier can be very useful when dealing with illumination changes. Indeed, the method used in BRIEF and FREAK relies on intensity differences between pairs of pixels and if both the intensities of a pair change in the same way the result of the test remains constant. However, the dataset used in this work contains images of the same scenes under different weather conditions and the illumination changes are not linear and uniform all over the images. The presence of shadows or, for instance, rain over the glass of the camera could modify only the intensity of one of the pixels subjected to the test of the descriptor, and then the result would be biased. Finally, another problem is related to the presence of clouds. Indeed, a special characteristic of the AMOS dataset is that many webcams partly point to the sky and then the sun and the clouds strongly modify the images. When training the random forest, no descriptor comes from an area of the sky where there might be clouds; however, the descriptors contain only values that indicate a sort of gradient associated to the pixel intensities and this gradient can be obtained also with different configurations.

3.1.6 Training of the neural network

As already mentioned before, while when training the random forest, a set of descriptors has been used, here patches centered at the locations obtained in the previous steps are extracted and directly used as training set, since descriptors are implicitly learned by the network. After the extraction of the patches pixel by pixel, it is necessary to create a dataset that will be used by the neural network. This dataset is obviously composed by all the patches, but it must also contain all the labels, associated with their corresponding images, that indicate to which class the sample

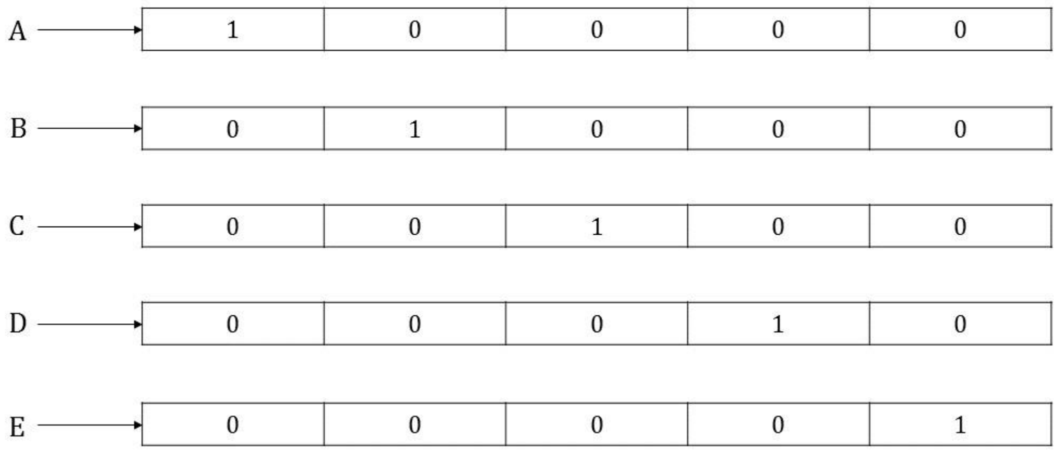


Figure 3-13. Example of one-hot encoding

belongs to. This thesis work is aimed at finding highly distinctive keypoints and to do that is necessary to analyze all the pixels of an input image and identify them as positive or negative. The classification approach to be used, then, is a binary classification that involves two classes.

The labels to be used can be of two different types:

- dense labels, which means that, in this specific case, it is necessary to assign a value to one class and another value to the other class; in this thesis work the label 1 is assigned to the positive samples while the label 0 to the negative ones;
- one-hot labels, which means that starting from a set of dense labels, a binary vector of 0s is created for each label and a 1 in different position identify a label. **Figure 3-14** shows an example.

In this work, a binary classification is required, thus it is possible to use both a simple dense labeling or a one-hot labeling. In case of multiclass classification, like, for instance, in the handwritten digit classification or letters classification, the one-hot encoding is necessary to identify each class using only 0s and 1s.

Chapter 2 explained how an image can be processed through the neural network by operators, like convolution, pooling, activation functions and dropout. The architecture that has been used in this thesis is shown in **Figure 3.14** and it is the same for both training and testing.

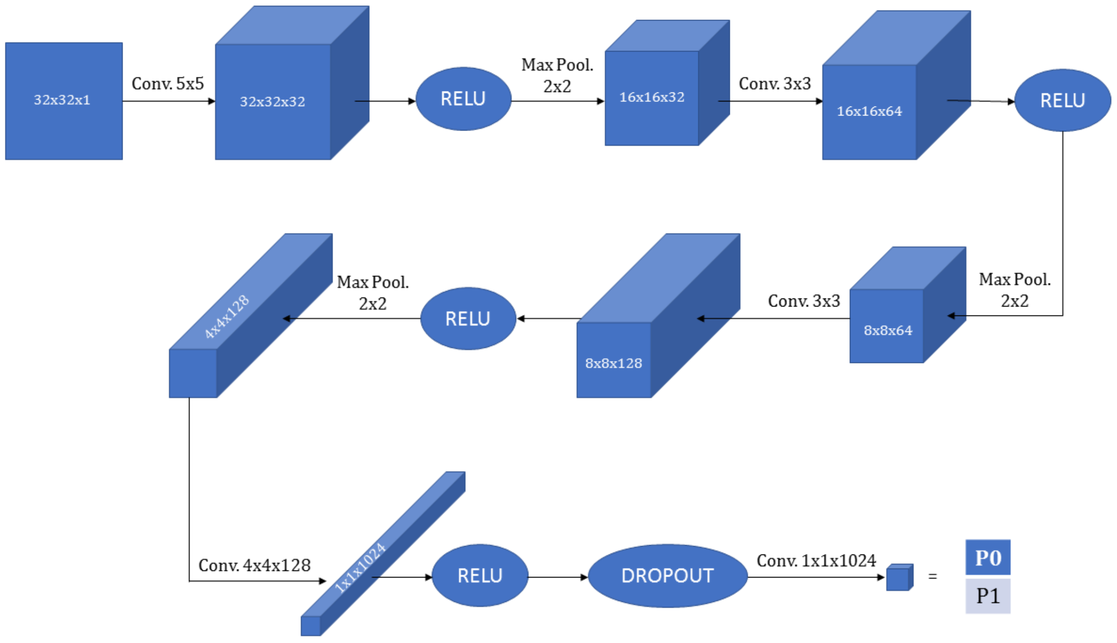


Figure 3-14. Architecture of the CNN

After having created a training dataset, composed by many 32x32 patches, the procedure for the training is the following:

1. Take the first image of the training dataset.
2. Apply 32 convolutions using a filter of size of 5x5; the output tensor (stack of images) has a size of 32x32x32. The size of every image after the convolution does not change because a padding is applied before the filter.

3. Apply the activation function. In this case, the REctified Linear Unit is used, but also the *tanh* can be used.
4. Apply a max pooling with a filter of size 2x2 and a stride of 2. The depth of the output remains constant while the size of every image is halved. The output has a size of 16x16x32.
5. Apply 64 convolutions using a filter of size of 3x3; the output tensor has a size of 16x16x64. The size of every image after the convolution does not change because a padding is applied before the filter.
6. Apply the activation function.
7. Apply a max pooling with a filter of size 2x2 and a stride of 2. The output has a size of 8x8x64.
8. Apply 128 convolutions using a filter of size of 3x3; the output tensor has a size of 8x8x128. The size of every image after the convolution does not change because a padding is applied before the filter.
9. Apply the activation function.
10. Apply a max pooling with a filter of size 2x2 and a stride of 2. The output has a size of 4x4x128.
11. Apply 1024 convolutions using a filter of size of 4x4x128; the output tensor has a size of 1x1x1024. The size of every image after the convolution changes because no padding is used.
12. Apply the activation function.
13. Apply dropout.
14. Apply 2 convolutions using a filter of size of 1x1x1024; the output tensor has a size of 1x1x2.
15. Compare the output of the network to the label associated with the input image and optimize the weights and the biases in order to minimize the cross entropy. The optimizer used in this thesis is the Adam optimizer.
16. Take the next image of the training set and repeat from step 2.

At the end of this process, every patch will have been analyzed and the set of weights and biases inside every convolution will have been updated depending on the loss function.

The framework that has been used in this thesis for the CNN is TensorFlow [12] that makes the creation and the training of a neural network very easy. The only thing to do, at the beginning of the code, is to create two placeholders: one for the input images and one for the labels associated with these images. Then it is necessary to create a function for the initialization of the weights from a truncated Gaussian distribution (other types of initialization can be used) and a function for the initialization of the biases to a small value different from zero. This last value and the standard deviation of the Gaussian curve are the same of the MNIST tutorial code provided by TensorFlow. This framework allows, also, to monitor the results of the neural network, how the weights and biases change and the output of every convolution. Inside the code, indeed, it is possible to use commands like "*tf.summary.image*" or "*tf.summary.histogram*" to keep track of the elements of the flow and then it is possible to visualize them using a tool called TensorBoard.

Figure 3-15 shows the first page of TensorBoard once it has been launched using the command "*tensorboard –logdir=path_to_logdir/logs*" and the web browser has been navigated to

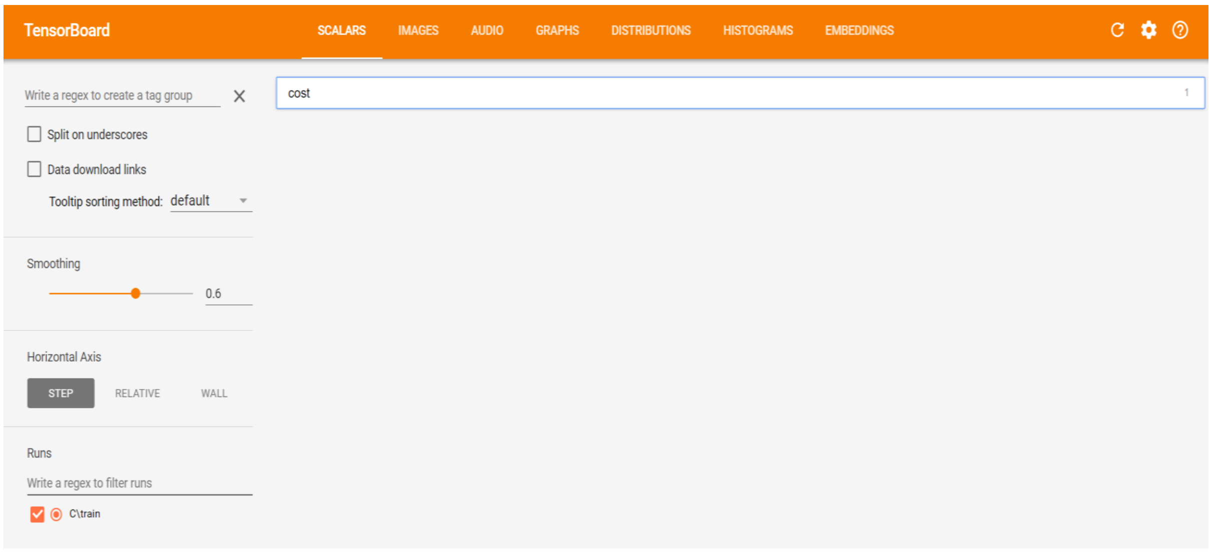
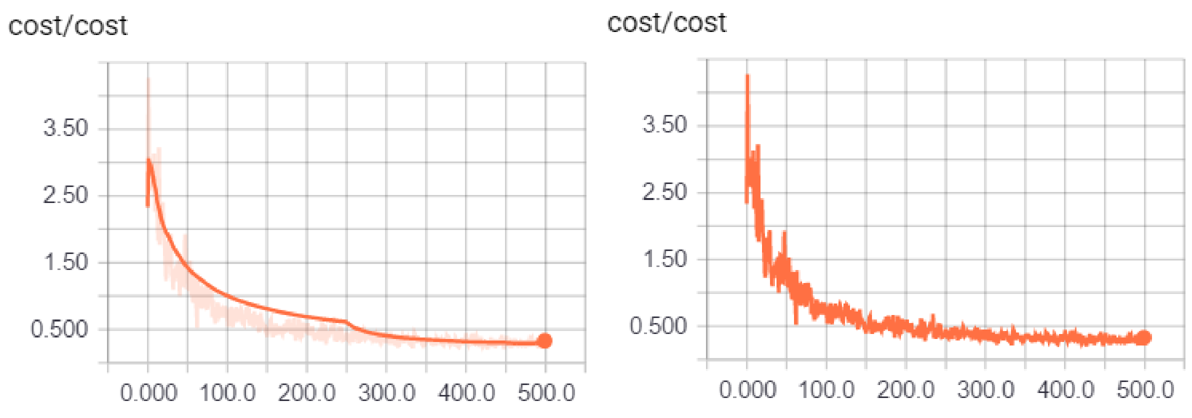


Figure 3-15. TensorBoard homepage

"*localhost:6006*". After having correctly configurated TensorBoard, it is possible to visualize the TensorFlow plots, images, graphs and other elements and this can be very useful for the understanding of the network, the debugging and the optimization. When visualizing plots of



(a) **(b)**

Figure 3-16. Cost function with (a) smoothing = 1 and (b) smoothing = 0

scalars, like the accuracy or the cost it is always possible to adjust the smoothing of the curve in order to understand better the real behavior of the data. Two very important parameters of the neural network are the batch size, namely how many images must be processed at every iteration and the total number of iterations. As it is shown in **Figure 3-16**, the number of iterations in that specific case is 500, while the used batch size is 100. These two parameters must be carefully chosen because a small batch size would need much more time to converge to a minimum, but can be more general, whereas a big batch size would behave in the opposite way. A good trade-off must be found by looking at the accuracy and the loss function that, in this case, is the cross entropy.

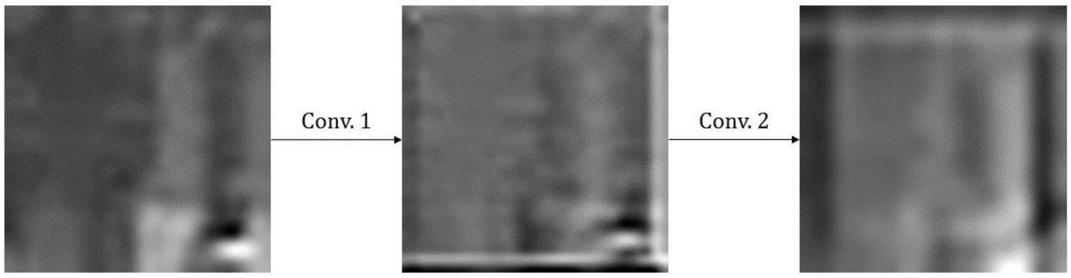


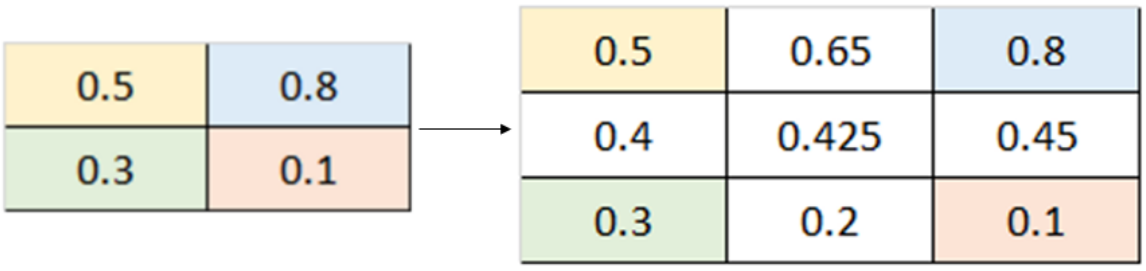
Figure 3-17. Example of convolutions applied to an input patch

After having trained the neural network, a test dataset is created from some test images. In this case, it is not necessary to extract the patches from the test images because the convolutions of the neural network work themselves on small areas of the input images. For instance, when testing the network on the Courbevoie webcam dataset, the size of every input images is 640x471, but there is no need to modify the network. However, the changes applied to the input images by the network are the same that have been used over the training sequence and then, if the training image height is halved by the max pooling layer, the test image height will be halved as well. At the end of the pipeline, instead of a 1x1x2 tensor, i.e. two probabilities, one for each class, there will be a heat-map with a probability for every pixel of the image. The procedure to be followed is the same of the training but with trained weights and biases and different sizes:

1. Take the first image of the test dataset (in this case with size 640x471).
2. Apply 32 convolutions using a filter of size of 5x5 with the trained weights and biases; the output tensor has a size of 640x471x32. The size of every image after the convolution does not change because a padding is applied before the filter.
3. Apply the activation function.
4. Apply a max pooling with a filter of size 2x2 and a stride of 2. The output has a size of 235x320x32.

5. Apply 64 convolutions using a filter of size of 3x3; the output tensor has a size of 235x320x64. The size of every image after the convolution does not change because a padding is applied before the filter.
6. Apply the activation function.
7. Apply a max pooling with a filter of size 2x2 and a stride of 2. The output has a size of 117x160x64.
8. Apply 128 convolutions using a filter of size of 3x3; the output tensor has a size of 117x160x128. The size of every image after the convolution does not change because a padding is applied before the filter.
9. Apply the activation function.
10. Apply a max pooling with a filter of size 2x2 and a stride of 2. The output has a size of 58x80x128.
11. Apply 1024 convolutions using a filter of size of 4x4x128; the output tensor has a size of 54x76x1024. The size of every image after the convolution changes because no padding is used.
12. Apply the activation function.
13. Apply dropout.
14. Apply 2 convolutions using a filter of size of 1x1x1024; the output tensor has a size of 54x76x2.
15. Take the next image of the test set and repeat from step 2.

The output of the last convolution is, then, no longer 1x1x2 as it was in the training step, but it is 54x76x2. The last dimension is 2 because we have the probabilities of belonging to one class instead of the other, but the only one we care about is the probability of belonging to the positive class. Therefore, we can slice the tensor and keep only the 1D heat-mat associated with the positive class. The problem now, is that we have to overlap the output heat-map with size 54x76 to the original test image with size 640x471 in order to find which pixels are positive and which are negative. After all the pooling and the convolutions, the 1 to 1 pixel correspondence is lost and, in this specific case, one element in the heat-map corresponds to a patch size of roughly 8x8 pixels. The solution to this problem is a simple image upsampling using bilinear interpolation. When resizing images from a lower dimension to a higher dimension the main problem is that the final image is made of many more pixels that were not there before. The intensity of these pixels must be inferred by looking at the intensities of the neighbor pixels. After the upsampling, then, the size of the heat-map is the same of the input test image and it is possible to extract the positive keypoints. To do that all the points with a probability greater than 50% are stored in a vector and then a non-maxima suppression is applied in order to keep as positive only the points with the highest response.



0.5	0.8
0.3	0.1

0.5	0.65	0.8
0.4	0.425	0.45
0.3	0.2	0.1

Figure 3-18. Example of upsampling

3.2 Validation

The training step requires, of course, the parameters to be set before it is executed, therefore it is necessary to find the best combination that allows to get the best results for the test images. The set of images that are used for the validation is a portion of the training dataset that is different with respect to the testing dataset. When the descriptors are placed inside the classifier, the result is a value that spans from -1 to +1, where +1 means that the input element belongs to the positive samples set with a probability of 100%, and -1 the opposite. So, it is necessary to define a threshold that identifies all the descriptors with a prediction value over such threshold as salient points. The validation process is executed in different ways depending on the type of parameter to be tuned. Up to now, the parameters to be validated for the random forest are:

- the sampling rate of the input training image;
- the non-maxima suppression radius for the training images;
- the matching type, i.e. straight, cross and cross-random matching;
- the number of trees and the two parameters of the tree depth;
- the threshold that defines positive and negative samples;
- the non-maxima suppression radius for the test images.

On the other hand, when dealing with the neural network, the parameters to be tuned are different; indeed, during the training step it is important to define the learning rate of the optimization algorithm, the number of iterations and the batch size that is randomly sampled from the training samples. After the computation of the probabilities for a test image and after having upsampled the heat-map, another parameter must be defined, namely the non-maxima suppression radius. The subsequent paragraphs explain the techniques used for the validation of the random forest and the CNN.

3.2.1 Training and test error

The first method used for the validation consists in computing the training and the test error of the matched images. This procedure is fundamental for the validation of two parameters of the random forest: the number of trees and the depth of the trees. First of all, all the other parameters are initialized to certain values, then the set features (the descriptors) associated with their labels is created and converted into a construct of OpenCV called TrainData. This cluster of training data is then split in two smaller groups: one to be used for the training and one for the validation. Now, using a for loop, it is possible to vary one parameter and keep the others fixed while training the random forest and computing the error on both the training set and the validation set. After having changed the parameter under analysis, the procedure is repeated for a range of possible values and, at the end, a list of errors is available and can be used to decide the best arrangement for the parameters. This approach is used for the validation of the following parameters:

- number of trees;
- tree depth;
- number of samples to be left at a node.

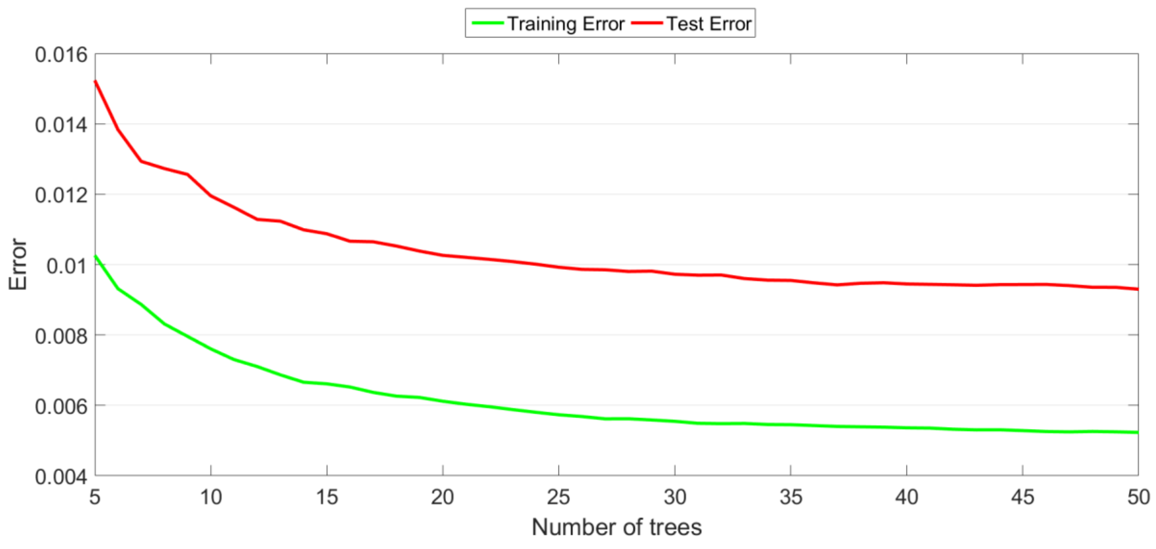


Figure 3-19. Example of training and test error with different numbers of trees

The main criterion to be used when deciding which is the best value for a specific parameter is usually the decreasing rate of the error curve, i.e. when the error stops decreasing is no longer necessary to increase or decrease the parameter that is being analyzed. However, another aspect must be kept into consideration; indeed, if the training error keeps decreasing while the validation error increases, the forest is suffering from overfitting, i.e. the machine learning algorithm is trained too much over the training data and can hardly manage new input data.

3.2.2 Precision-Recall curve

The second approach is based on the computation of the Precision-Recall curve, a very useful tool for binary classification that measures the performances of a searching algorithm by looking at the amount of the correct information retrieved and the mistakes made while searching for that correct information. This method can be used both for the validation of some parameters of the random forest, similarly to what has been done with the parameters listed at the end of this subchapter, and for the comparison of the result of many keypoint detectors in terms of matchability.

Given a list of matches it is possible to compute two very important indices:

- the precision, which is the fraction of the elements taken into account that are relevant to our purpose;
- the recall, which is the fraction of the relevant elements that are retrieved.

Basically, after having sampled the first image of the dataset and after having computed the descriptors over the sampled points, the random forest trained with a certain set of initial parameters is applied to every image of the dataset and a matching algorithm is used in order to find the best nearest neighbor for every descriptor of the first image and all the others. For every matched pair, the distance between the two descriptors is normalized using the maximum distance that two binary descriptors can have, that is the length of the description vector, and if the match is correct it is put inside the true positives (TP) set, while if it is wrong it is put inside the false positives (FP) set.

By varying a threshold over the distance between the descriptors to accept a match, the values for "1 - Precision" and Recall are computed using the following formulas:

$$1 - Precision = \frac{FP}{TP+FP} \ , \tag{3-1}$$

and

$$Recall = \frac{TP}{P} \ , \tag{3-2}$$

where P is, in this case, the total number of matches, i.e. the total number of sampled points. Once the curves have been created, the best one is selected by looking at the area under the curve (AUC) and the highest its value, the better the set of used parameters. **Figure 3-20** shows an example of comparison between two models with a different threshold applied to the random forest to accept the positive elements; the AUC of the red curve is higher with respect to the AUC of the blue one and then a threshold equal to 0.5 should be chosen.

The dataset used for the computation of the precision-recall curve must be different from the training dataset, of course. The splits between training, validation and test datasets used in this work are the same used in TILDE and then, the number of images is 100 for the training dataset, 20 for the validation and 20 for the test. All the images are different because of the different weather and illumination conditions, but the scene is always the same since the pictures come from fixed webcam.

This precision-recall method is used for the validation of the following parameters:

- the sampling rate of the input training image;
- the non-maxima suppression radius for the training images;
- the matching type;
- the threshold that defines positive and negative samples;
- the non-maxima suppression radius for the test images.

Finally, the Precision-Recall curves are also used to compare the method proposed in this work to TILDE in order to contrast the performances of the whole detection-description-matching pipeline.

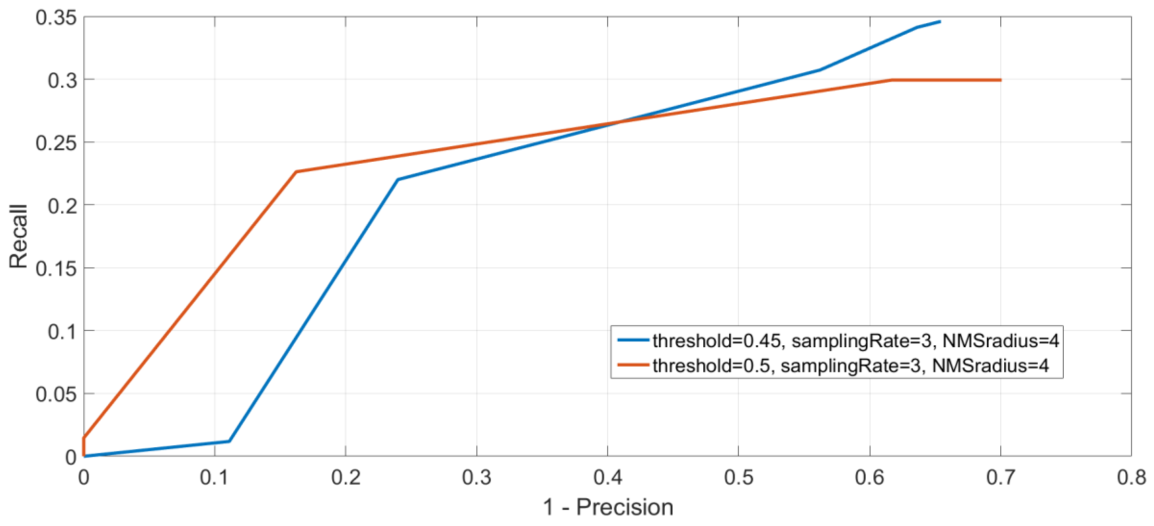


Figure 3-20. Example of 1 - Precision / Recall curve

CHAPTER 4
RESULTS

This chapter presents in detail the results obtained in this thesis work. The first two parts illustrate the validation of the parameters of random forest and convolutional neural network, the third part shows the results obtained during the testing step, while the last part shows the results from the comparison between the methods developed in this thesis and the TILDE keypoint detector.

4.1 Positive and negative sample extraction

The first step of the algorithm is the extraction of the positive and negative samples from the dataset. As already mentioned in the previous chapter, the most important parameters to be validated in this step are the ones related to the extraction of the training points, i.e. the sampling rate of the input images along with its non-maxima suppression radius, the type of matching to use and the type of descriptor. The parameters used here will be the same for both the random forest and the CNN, since this first part is common to both the approaches. The speed here is not very important since the extraction of the positive and negative samples and the training of the classifiers can be executed offline without any influence on the online performance. However, a faster training is always better in terms of practicability. **Table 4-1** shows the speed, in seconds, for every combination of parameters of the sample extraction.

Table 4-1. Speed comparison of all the combinations of parameters

SAMPLING RATE + NMS radius		3 + 8		5 + 8		8 + 0	
MATCHING TYPE	**DESCRIPTOR TYPE**	BRIEF	FREAK	BRIEF	FREAK	BRIEF	FREAK
STRAIGHT		800s	1500s	100s	200s	20s	35s
CROSS 30		3500s	7000s	440s	800s	90s	150s
CROSS-RANDOM 5		4400s	8400s	500s	1000s	100s	180s

It is possible to see that the aspects to consider when analyzing the speed of the algorithm are multiple. Indeed, all the parameters have their own influence; for instance, the sampling rate has a strong influence on speed since changing its value from 3 to 5 halves the time and from 5 to 8 the speed is more than doubled. The matching type is also very important, because each method analyzes a number of images that varies; indeed, the straight matching compares only the first image of the training dataset to all the others and, since the dataset size is 100 images, the number of comparisons will be 99. The second matching type analyzes all the combinations among 30 images which means 435 comparisons, while the cross-random method uses 5 randomly chosen images for every image of the dataset, i.e. 500 comparisons. Finally, the descriptor type is important because of the extraction of the descriptors, but also for the matching step. As already mentioned in Chapter 2, BRIEF descriptor tests less pairs with respect to FREAK so it is faster in this first step, but when the matching must be executed the comparison between FREAK descriptors is faster due to their structure.

Once the positive and negative samples are extracted it is possible to see the qualitative results by looking at the locations that have been detected. For instance, **Figure 4-1** shows a comparison between three different types of samples extraction. In the first two images, it is used a small sampling rate plus a non-maxima suppression in order to avoid too dense clusters of points, while in the last one it is used a sampling rate equal to 8 without any NMS.

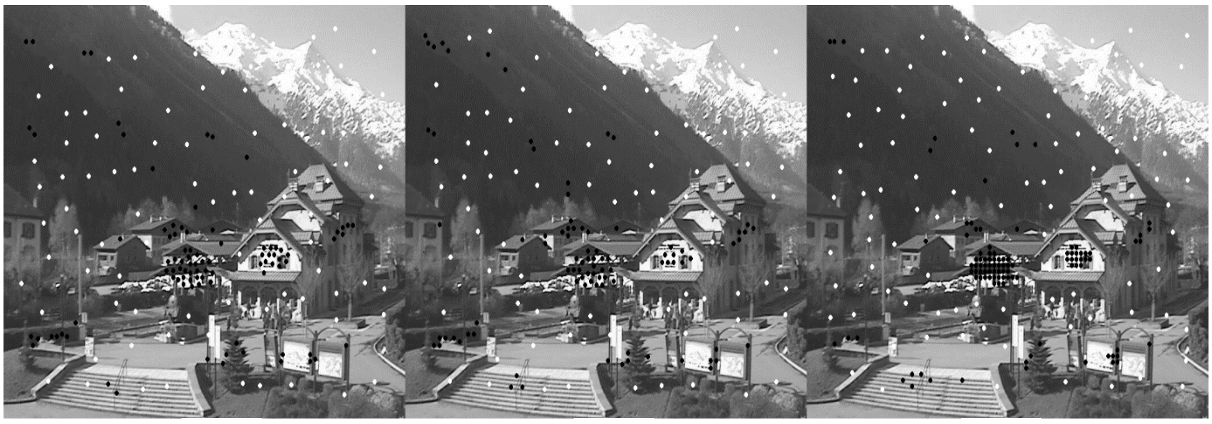


Figure 4-1. Comparison between sample extraction using BRIEF and a straight matching with (a) sampling rate 3, (b) sampling rate 5, (c) sampling rate 8. The black dots are positive samples while the white dots are the negatives.

Usually, the best points to be found should be the ones in very distinctive locations that can be easily found over the image and the points that are surrounded by specific shapes, like, for instance, corners or blobs. However, the approach used in this thesis wants to find points that present a very high descriptor distinctiveness and not a high repeatability. When two descriptors are matched, one of the most important things is the way they have been described which is, in this case, either using BRIEF or FREAK. **Figure 4-2** shows a comparison between two images: the first is obtained using BRIEF, while the second using FREAK. It is easy to note that both the

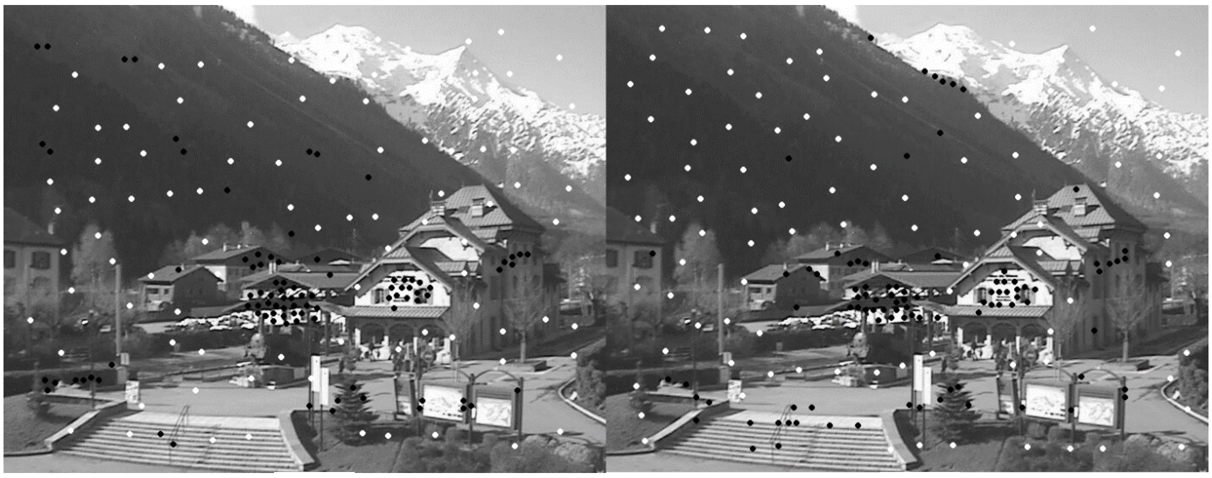

(a) **(b)**

Figure 4-2. Positive (in black) and negative (in white) points obtained using (a) BRIEF description and (b) FREAK description

positive and the negative locations are different. The reason behind this is that a different type of descriptor can make a point easier to be found when matched to another point, not because of the different way of comparing the two vectors, but because the distribution of intensities that is analyzed can be more similar to a vector of description that does not correspond to the right correspondence. In other words, when matching a pair of images, due to a reduced distinctiveness of the description vector, a point can be associated with a wrong corresponding location, and this generates different errors. For instance, in **Figure 4-2 (a)**, where BRIEF descriptor is used, a dozen positive points are detected over the dark mountain on the left in an apparently non-salient area, while in the image on the right, only three points are detected over the mountain but six can be found on the edge of the mountain. Another difference is the number of points on the stairs that is higher when using FREAK. The positive samples on the front of the house, instead, are detected independently with respect to the used descriptor.

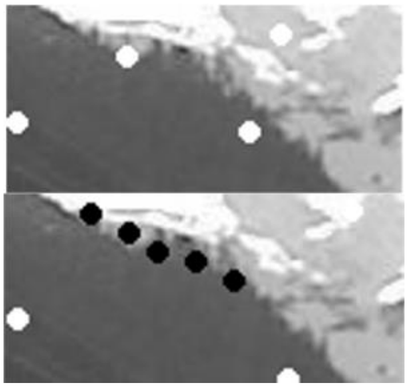


Figure 4-3. Positive (in black) and negative (in white) samples using BRIEF (up) and FREAK (down)

Another important aspect to consider when judging whether a sample extraction is good or not is the position of the negative samples. The white dots of the images are randomly sampled over

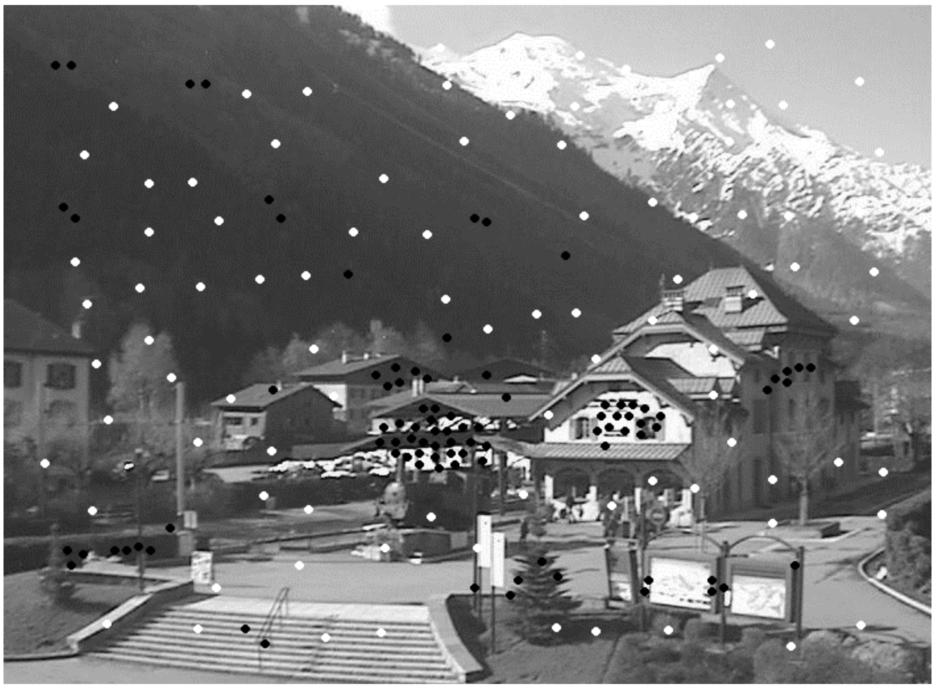


Figure 4-5. Positive (in black) and negative (in white) samples using the straight matching

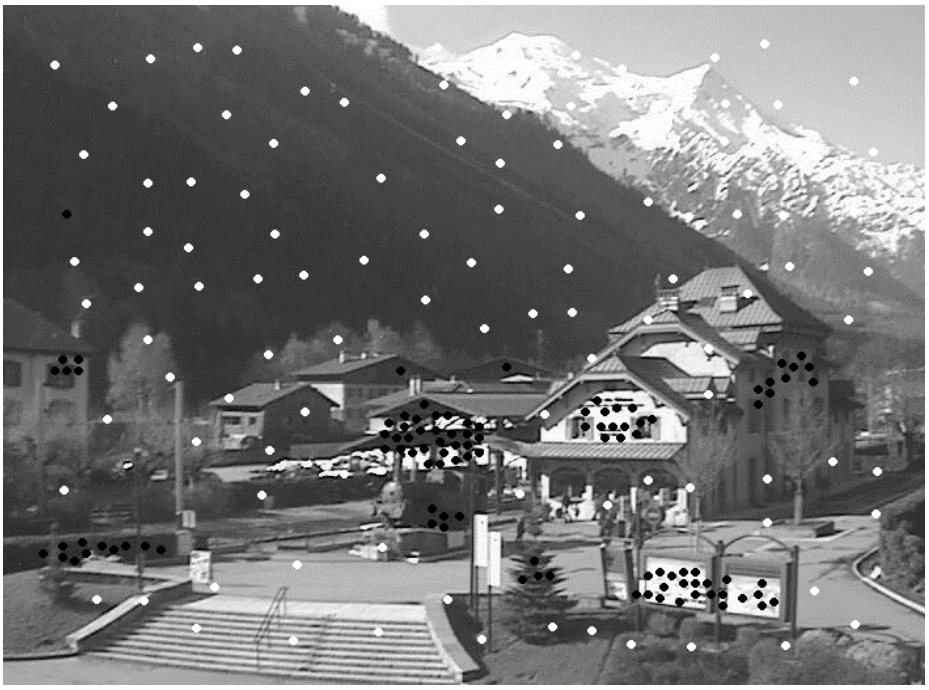


Figure 4-4. Positive (in black) and negative (in white) samples using the cross matching

the image in such a way that they are at least 30 pixels far from all the positive points and all the negative points. In this way, it is possible to cover the entire image and there is no overlapping between the patches around these points. By looking at **Figure 4-2** it is possible to see that on the edge of the darker mountain, BRIEF randomly picks some negative locations, while FREAK finds some positive samples and then cannot pick negatives in that area. This will have consequences both when using the random forest and when using the neural network as classifier.

Finally, **Figure 4-4**, **Figure 4-5** and **Figure 4-6** show the results obtained using the three matching types created in this thesis work.

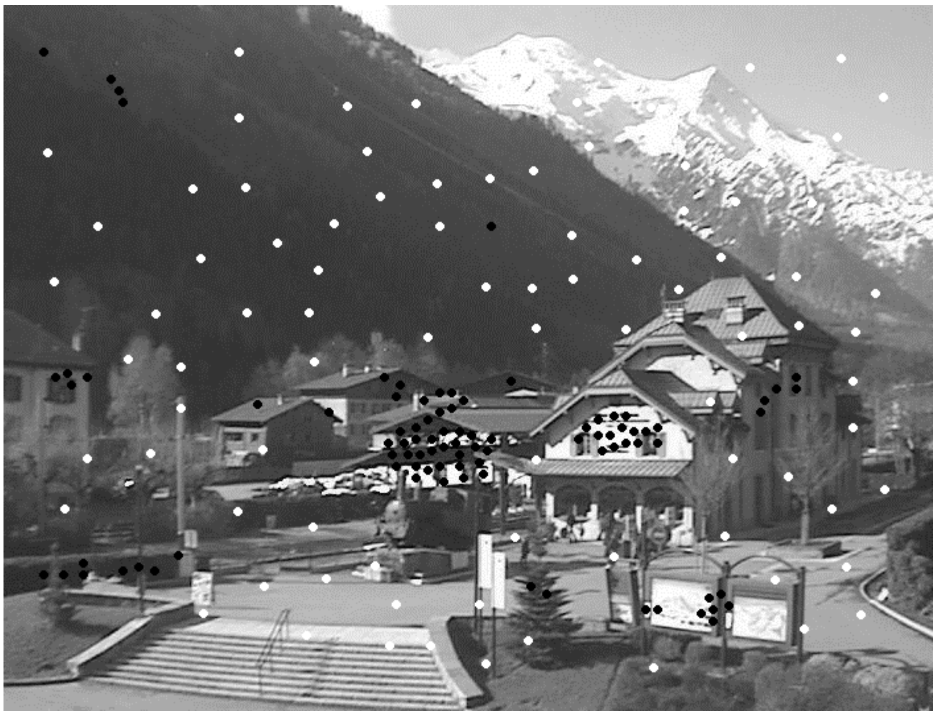


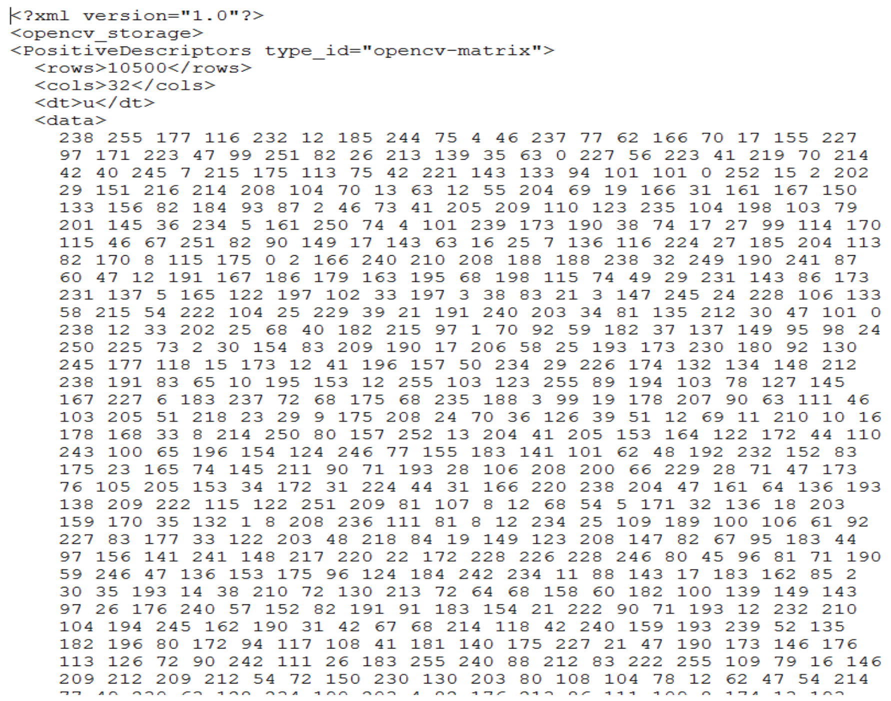
Figure 4-6. Positive (in black) and negative (in white) samples using the cross-random matching

4.2 Training

After having found the positive and negative locations, it is possible to use them in order to train the classifier. In this work, the classifiers that have been used are a random forest and a convolutional neural network. In the first case the features to be used for the training of the classifier are the descriptors computed at the sample coordinates over the images of the training dataset; in the second case, there is no need for some a priori defined features since the network, given a set of input patches with their correspondent labels, can autonomously infer some specific patterns. The following subchapters show in detail the results of the parameter tuning for the two classifiers.

4.2.1 Random forest

As already mentioned, the random forest is trained using the descriptors computed at the positive and negative locations. These descriptors are already available because they have been previously stored during the extraction of the samples. The only thing to do, then, is to create a dataset suitable for the construct of the random forest in OpenCV.



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<?xml version="1.0"?>
<opencv_storage>
<PositiveDescriptors type_id="opencv-matrix">
  <rows>10500</rows>
  <cols>32</cols>
  <dt>u</dt>
  <data>
    238 255 177 116 232 12 185 244 75 4 46 237 77 62 166 70 17 155 227
    97 171 223 47 99 251 82 26 213 139 35 63 0 227 56 223 41 219 70 214
    42 40 245 7 215 175 113 75 42 221 143 133 94 101 101 0 252 15 2 202
    29 151 216 214 208 104 70 13 63 12 55 204 69 19 166 31 161 167 150
    133 156 82 184 93 87 2 46 73 41 205 209 110 123 235 104 198 103 79
    201 145 36 234 5 161 250 74 4 101 239 173 190 38 74 17 27 99 114 170
    115 46 67 251 82 90 149 17 143 63 16 25 7 136 116 224 27 185 204 113
    82 170 8 115 175 0 2 166 240 210 208 188 188 238 32 249 190 241 87
    60 47 12 191 167 186 179 163 195 68 198 115 74 49 29 231 143 86 173
    231 137 5 165 122 197 102 33 197 3 38 83 21 3 147 245 24 228 106 133
    58 215 54 222 104 25 229 39 21 191 240 203 34 81 135 212 30 47 101 0
    238 12 33 202 25 68 40 182 215 97 1 70 92 59 182 37 137 149 95 98 24
    250 225 73 2 30 154 83 209 190 17 206 58 25 193 173 230 180 92 130
    245 177 118 15 173 12 41 196 157 50 234 29 226 174 132 134 148 212
    238 191 83 65 10 195 153 12 255 103 123 255 89 194 103 78 127 145
    167 227 6 183 237 72 68 175 68 235 188 3 99 19 178 207 90 63 111 46
    103 205 51 218 23 29 9 175 208 24 70 36 126 39 51 12 69 11 210 10 16
    178 168 33 8 214 250 80 157 252 13 204 41 205 153 164 122 172 44 110
    243 100 65 196 154 124 246 77 155 183 141 101 62 48 192 232 152 83
    175 23 165 74 145 211 90 71 193 28 106 208 200 66 229 28 71 47 173
    76 105 205 153 34 172 31 224 44 31 166 220 238 204 47 161 64 136 193
    138 209 222 115 122 251 209 81 107 8 12 68 54 5 171 32 136 18 203
    159 170 35 132 1 8 208 236 111 81 8 12 234 25 109 189 100 106 61 92
    227 83 177 33 122 203 48 218 84 19 149 123 208 147 82 67 95 183 44
    97 156 141 241 148 217 220 22 172 228 226 228 246 80 45 96 81 71 190
    59 246 47 136 153 175 96 124 184 242 234 11 88 143 17 183 162 85 2
    30 35 193 14 38 210 72 130 213 72 64 68 158 60 182 100 139 149 143
    97 26 176 240 57 152 82 191 91 183 154 21 222 90 71 193 12 232 210
    104 194 245 162 190 31 42 67 68 214 118 42 240 159 193 239 52 135
    182 196 80 172 94 117 108 41 181 140 175 227 21 47 190 173 146 176
    113 126 72 90 242 111 26 183 255 240 88 212 83 222 255 109 79 16 146
    209 212 209 212 54 72 150 230 130 203 80 108 104 78 12 62 47 54 214
```

Figure 4-7. Example of an xml file containing the descriptors used for the training of the forest

In this step the validation of three parameters takes place:

- number of trees to be used inside the random forest;
- maximum depth of every tree of the random forest;
- minimum number of samples to be left at a node.

The range of values used for every parameter is different; indeed, the number of trees varies from 0 to 95, the maximum depth from 10 to 40 and the number of samples from 30 samples to 1. The default values for the parameters of the random forest in OpenCV are: 5 for the maximum depth, 10 for the minimum samples required at a node for it to be split and 50 for the number of trees. **Figure 4-8** shows the error curve associated with a training set, composed by roughly 15000 elements, and the test error curve from a test dataset of about 3500 descriptors. The behavior of the two distributions is quite similar but shifted of approximately 0.1 points over the y-axis. This is because, of course, the error computed over the dataset used to train the forest will always be lower than the error computed training the forest over one dataset and computing the error over a different dataset. Regarding the number of trees to be used in the random forest, it is possible to note in **Figure 4-8** that the error decreases with a very low rate after 30 trees and, even if it gets better and better after this point, it is important to consider that the number of trees increases the prediction time linearly. Another important parameter is the maximum depth that every tree has; **Figure 4-9** shows how the training and test error varies with respect to a maximum depth range between 10 and 40. It is possible to note that the training error decreases smoothly and it completely stops decreasing when using 24 levels or more. On the other hand, the test error reaches its minimum at the 19th level, but it immediately gets back to a higher value and then it remains constant except for a small fluctuation around the 24th level. When the training error goes down but the test error increases, the classifier is overfitting the dataset and then it is necessary to stop. The maximum depth that will be used for the training of the forest is, then 18.

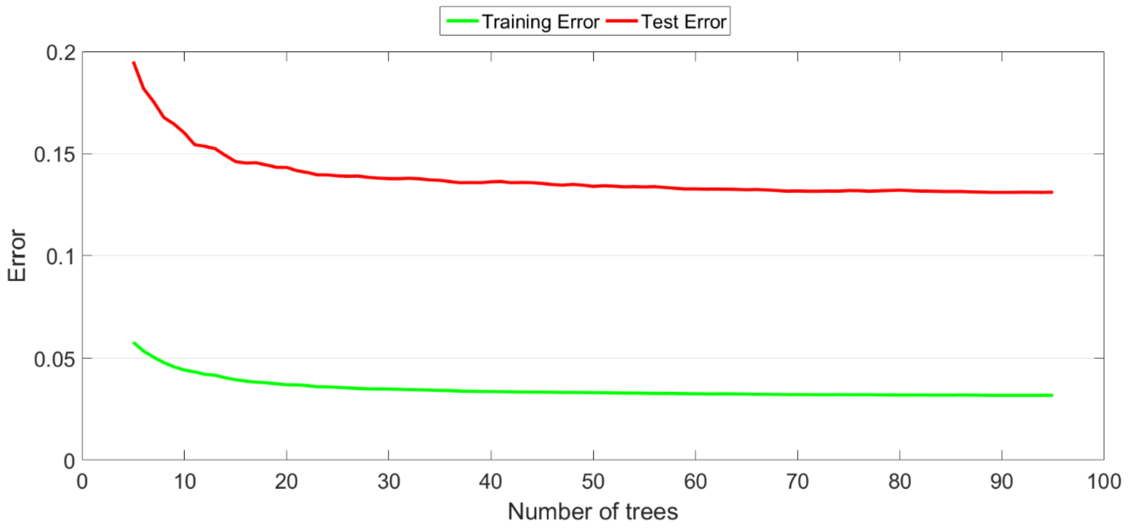

Figure 4-8. Training and test error when using a different value for the number of trees

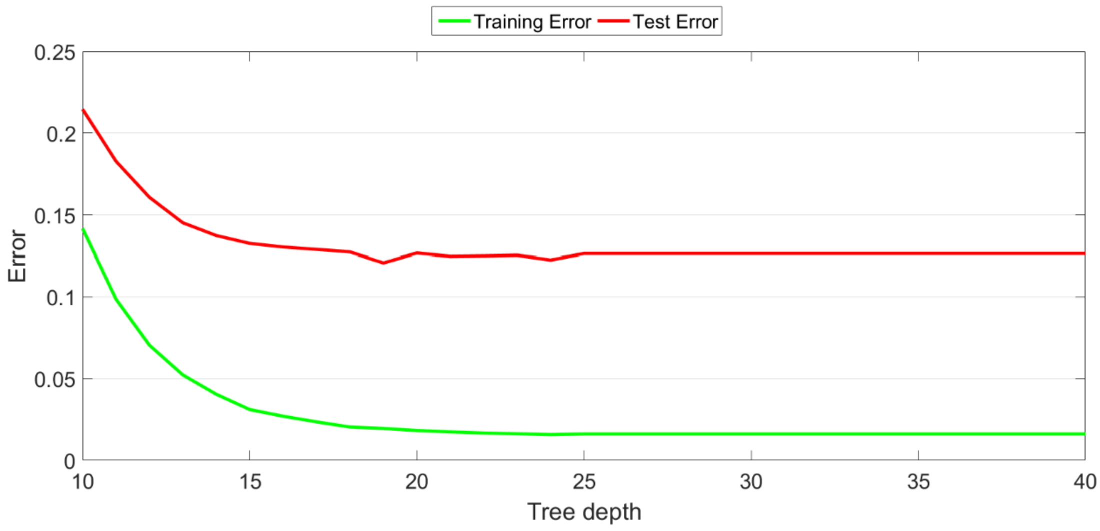

Figure 4-9. Training and test error when using a different value for the depth of the trees

Finally, the number of samples to be left at a node is chosen to be 3 because, while the training curve keeps decreasing with an almost linear trend, the test error curve fluctuates even if the general trend is always the same except for the last part where it starts increasing. Moreover, the training error over the last values used for the samples stops decreasing with a constant rate.

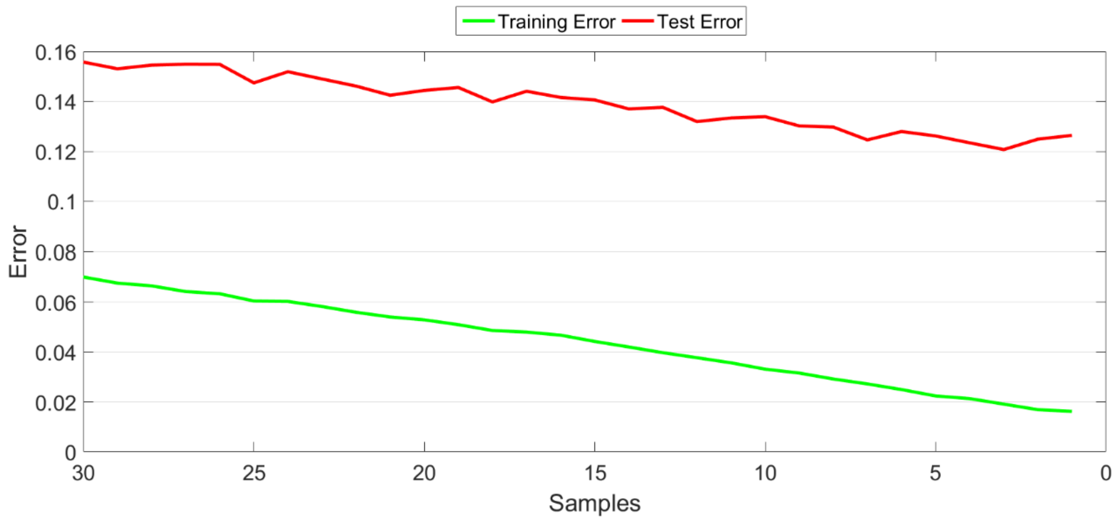

Figure 4-10. Training and test error when using a different value for the number of samples to be left at a node

Now it is possible to train the forests using the set of descriptors obtained during the positive and negative sample extraction with the parameters that have been validated, i.e. 30 trees, a maximum depth of 18 levels and a minimum number of samples at a leaf node equal to 3. At this point, the only parameters that still needs to be validated are the matching type and the sampling

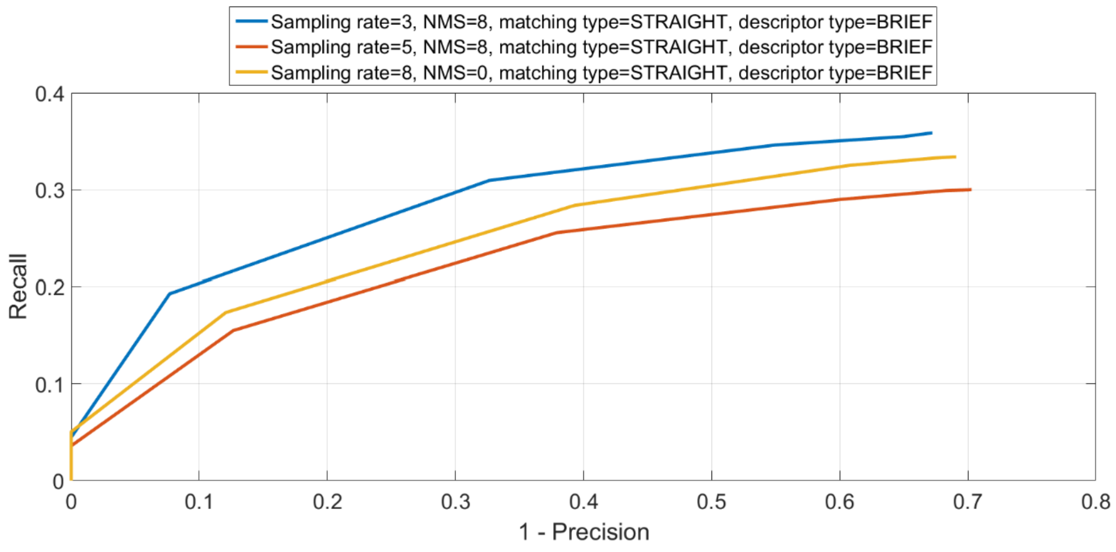

Figure 4-11. Comparison between precision-recall curves obtained using the straight matching type and different sampling rates

rate of the training images. To do that, the precision-recall curve and its area under the curve have been used: the higher the AUC the better the set of used parameters. **Figure 4-11** shows the comparison between three curves obtained using the same matching type, the same descriptor type, but different sampling rates of 3, 5 and 8 respectively. It is easy to see that the lowest sampling rate gives the best result, with an AUC of 0.19. Note that the highest sampling rate is not the worst; indeed, using a sampling rate of 5 with a non-maxima suppression radius of 8 gives an AUC equal to 0.15, while a higher sampling rate of 8 without any NMS gives an AUC equal to 0.17. **Figure 4-12** shows a comparison between different sampling rates with the cross-random matching type; note that, in this case, the lowest sampling rate does not give the best result

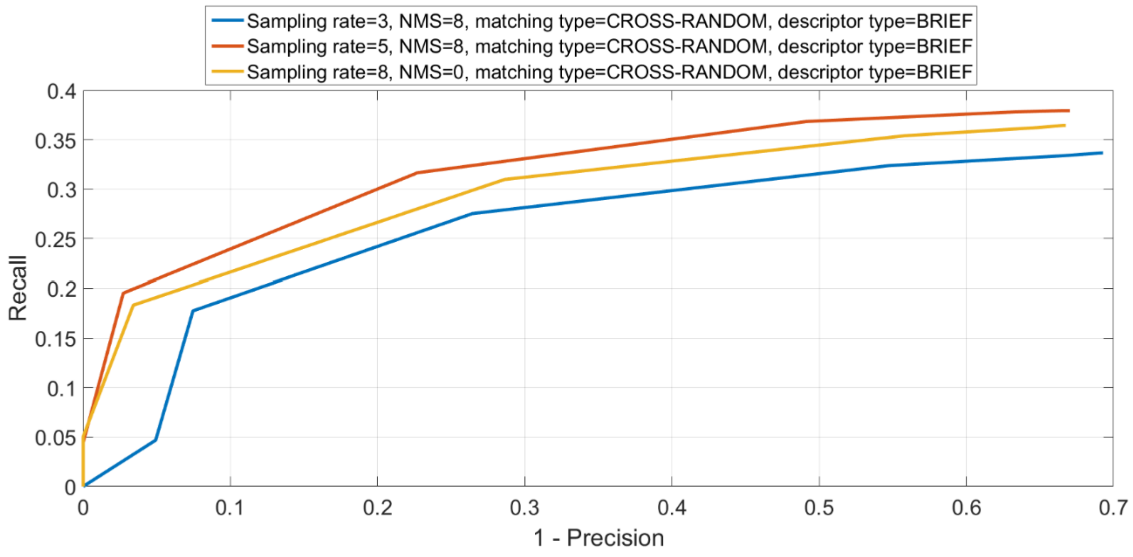

Figure 4-12. Comparison between precision-recall curves obtained using the cross-random matching type and different sampling rates

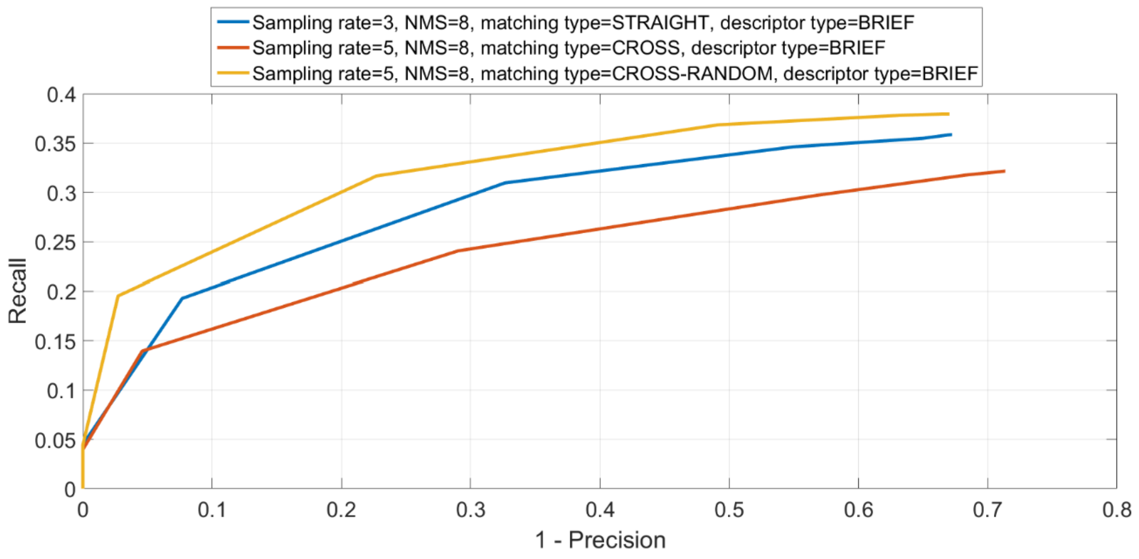

Figure 4-13. Comparison between precision-recall curves obtained using different matching types

because its AUC is the lowest among the three. The best result is obtained with a sampling rate of 5 and a non-maxima suppression of 8. In the case of cross matching type, the best result is again achieved using a sampling rate equal to 5 and a NMS equal to 8. Finally, the three matching types can be compared using the best combination of parameters for each of them and, as shown in **Figure 4-13**, the best result is achieved using the cross-random matching type with a sampling rate equal to 5 and a NMS equal to 8. Even if both the descriptor types will be used in the final step, it is interesting to see which one performs better on a validation dataset. **Figure 4-14** shows a comparison between two precision-recall curves obtained using BRIEF and FREAK descriptors, while **Figure 4.15** shows an example of prediction on an image from the validation dataset. The difference between the two methods strongly depends on the prediction threshold that is chosen, because if the same value is used a descriptor type can find either too few keypoints or too many. Another aspect to consider is the time: while BRIEF can be applied quickly over every pixel of the image, FREAK requires more time and can be very slow. A good alternative would be to sample the test images in order to have less points to be analyzed and, then, speed up the process. In this case, it is necessary to lower the prediction threshold because otherwise too few points are detected. The best result to achieve is with the BRIEF descriptor, because its AUC is equal to 0.13 versus an AUC of 0.8 and 0.75 for the other two curves. Note that a variation of only 0.05 points of the area under the curve of the FREAK descriptor applied to a sampled test image makes the detection faster of almost 25 seconds.

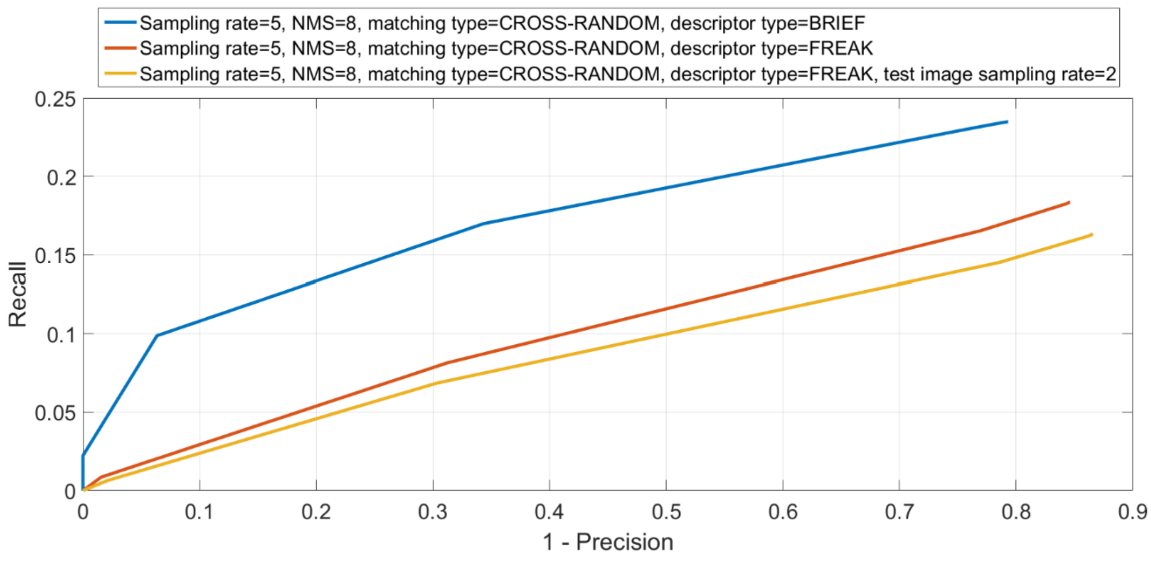

Figure 4-14. Comparison between precision-recall curves obtained using different descriptor types

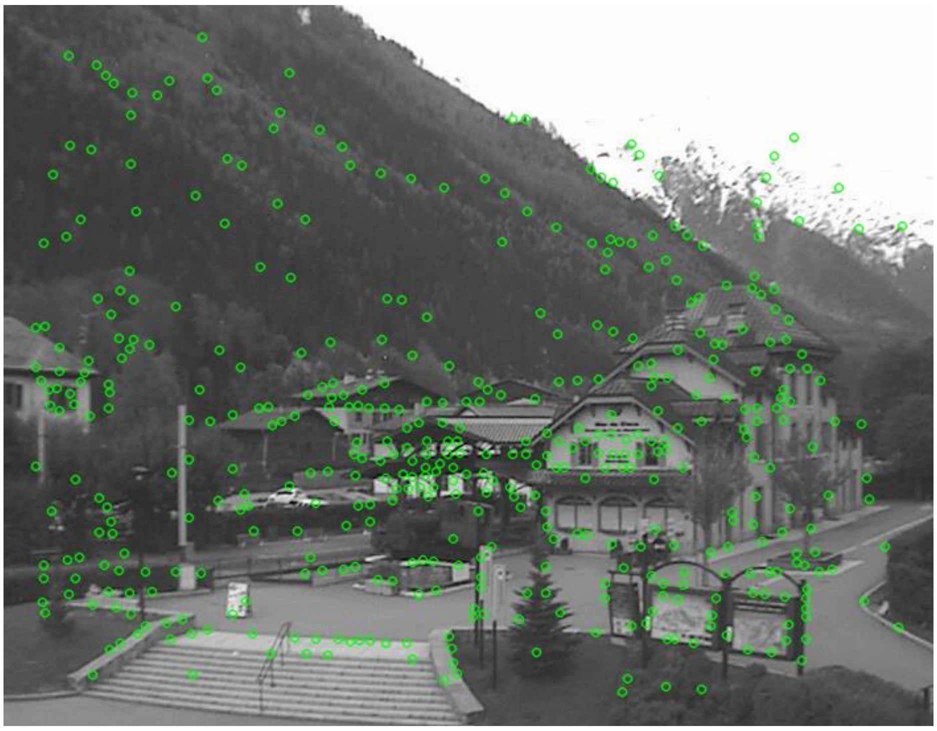
Figure 4-15. Random forest prediction over a validation image

4.2.2 Convolutional neural network

The training of the CNN, already explained in Chapter 3, is executed using the patches extracted from the positive and negative locations. One of the inputs to the preprocessing code written in Python consists of a pair of text files containing a list of coordinates for both the positive and the

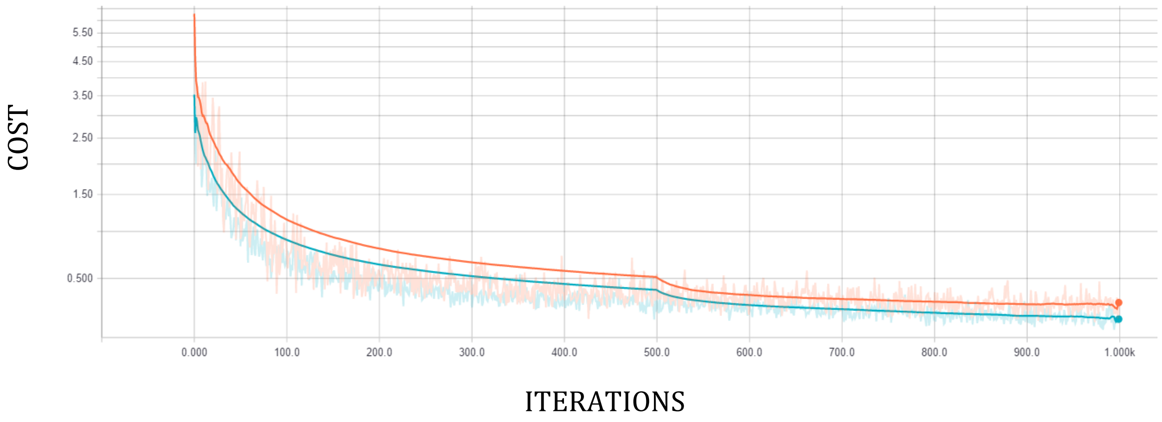

Figure 4-16. Comparison between a batch size of 50 (orange) and a batch size of 100 (blue)

negative samples. The parameters to be tuned in the CNN are the learning rate of the network, the number of iterations and the batch size. These parameters can be tuned by looking at the cost function that the network is trying to minimize and by stopping when the lowest cost is reached. The validation of the CNN requires, of course, some positive and negative locations; therefore, one among the set of already extracted sample points must be randomly chosen. **Figure 4-16** shows a comparison between the cost function obtained using a batch size of 50 and 100 and a number of iterations equal to 1000. It is possible to note that using a lower number of iterations is not convenient since the cost keeps decreasing with a consistent rate until 1000 iterations. Here, in the same way as in the random forest, the training step is entirely an offline process and then the time required is not so important. However, the neural networks require a lot of time to learn all the weights and biases and it is convenient, from a practical point of view, to get the best result in the lowest timing. **Table 4-2** shows a comparison of the costs obtained by playing with the parameters along with the timings required. A very fast training, like the one with 300 iterations and a batch size of 50, does not allow the network to learn the best weights and the biases for a very low prediction error, while with many iterations the cost function can reach lower values and better predictions.

Table 4-2. Comparison of all the combinations of parameters

NUMBER OF ITERATIONS	BATCH SIZE	LEARNING RATE	FINAL COST	TIME
300	50	1e-4	0.65	4m 26s
	100	1e-4	0.52	9m 14s
		1e-2	0.87	9m 31s
500	50	1e-4	0.49	7m 33s
	100	1e-4	0.24	15m 27s
		1e-2	0.26	15m 45s
700	50	1e-4	0.22	10m 17s
	100	1e-4	0.25	21m 40s
		1e-2	0.05	21m 36s
1000	50	1e-4	0.28	14m 56s
	100	1e-4	0.17	30m 53s
		1e-2	0.08	30m 44s

4.3 Test

Once all the parameters have been validated, it is possible to test the two trained classifiers over a new input dataset. Some of the previously mentioned parameters have not been tested yet, because they depend on the test dataset itself like, for instance, the prediction threshold to be used in the random forest. The images used for the testing step come from the AMOS dataset like the ones used for the training of the classifiers, but from another fixed webcam over different scenes.

At the end of the whole training and validation process, the three methods used during the test are:

- a random forest trained with the BRIEF descriptors computed at the positive and negative samples obtained using a sampling rate of 5 pixels and a NMS radius of 8 pixels;
- a random forest trained with the FREAK descriptors computed at the positive and negative samples obtained using a sampling rate of 5 pixels and a NMS radius of 8 pixels;
- a CNN trained using the patches extracted at the positive and negative samples obtained using a sampling rate of 5 pixels and a NMS radius of 8 pixels.

In order to speed up the process, since the difference of area under the curve during the validation was not so high, when extracting the FREAK descriptors over unseen input images, these images

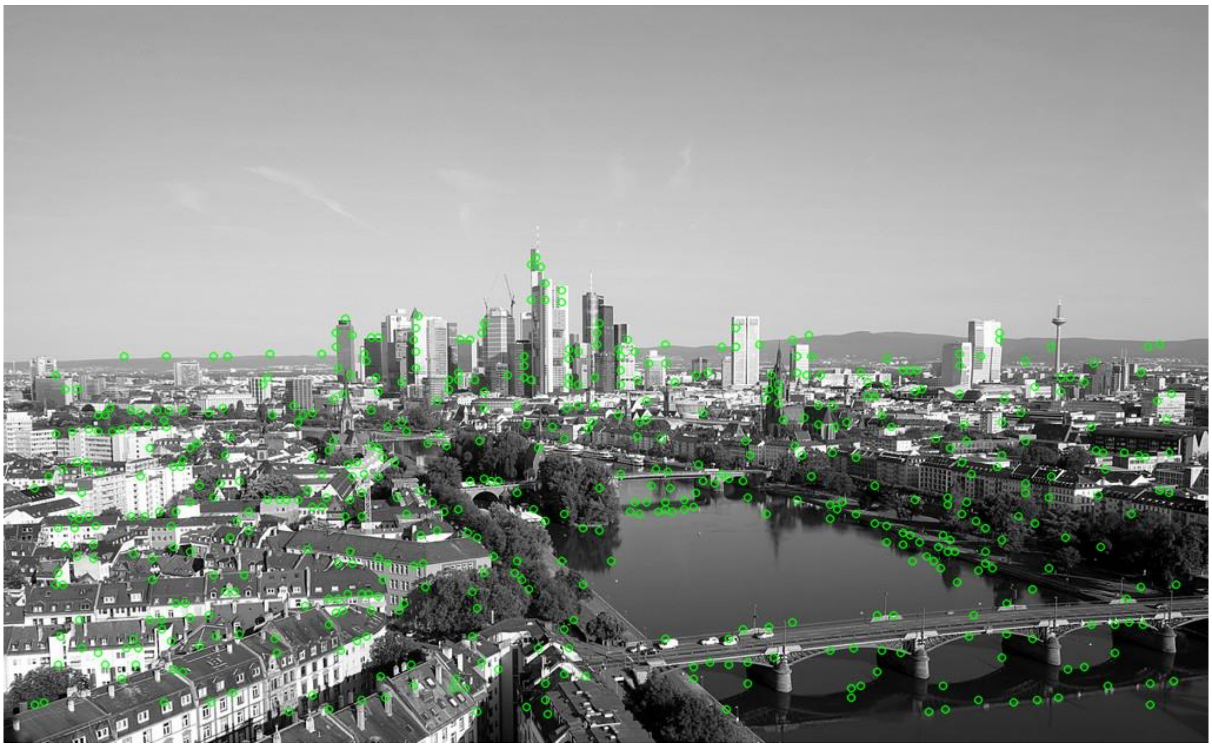

Figure 4-17. Random forest prediction using FREAK descriptors on an image from the Frankfurt webcam

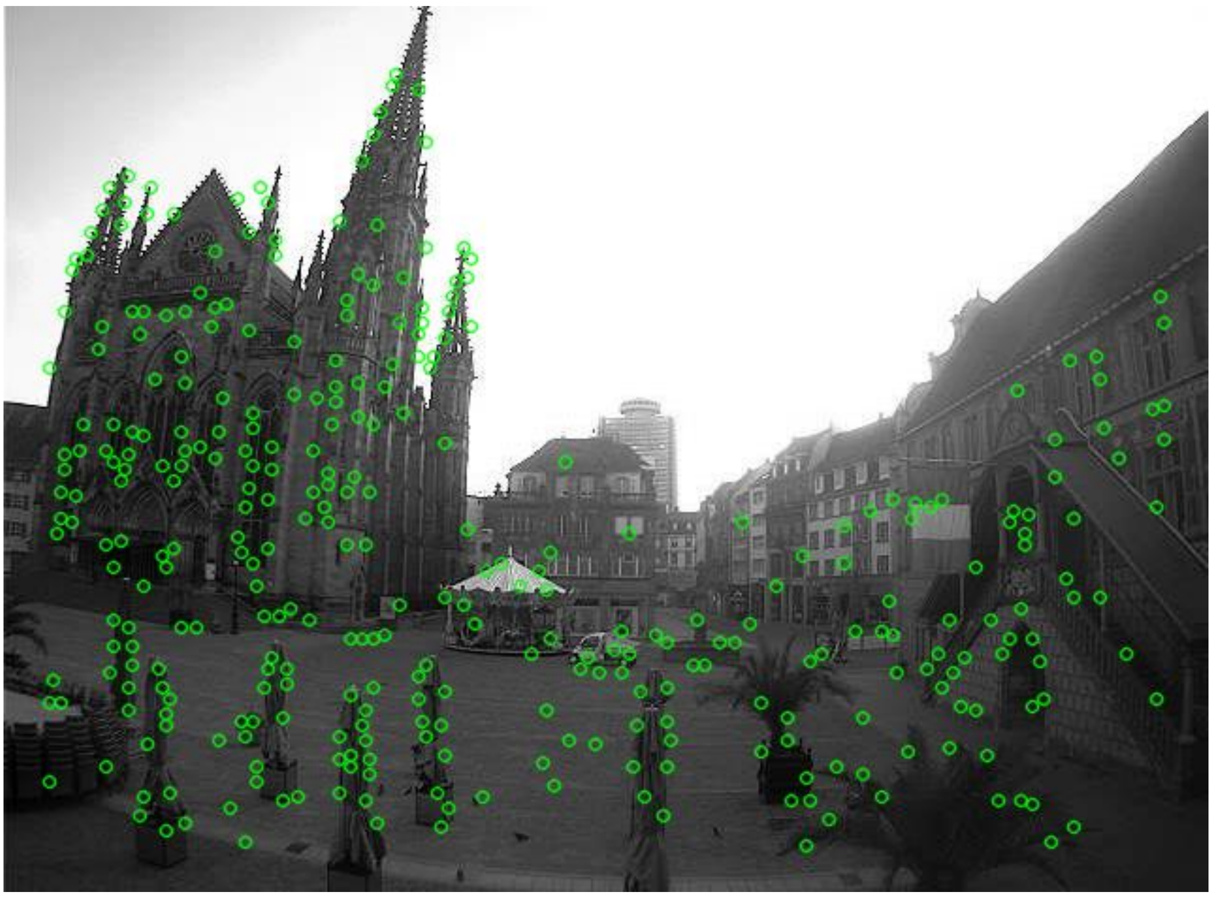
Figure 4-18. Random forest prediction using FREAK descriptors on an image from the Courbevoie webcam

are regularly sampled with a sampling rate equal to 2. **Figure 4-17** and **Figure 4-18** show some qualitative examples obtained using the random forest classifier with the FREAK descriptor.

When analyzing an image in a qualitative manner, it is important to define as good the keypoints in specific positions, because the saliency of the points and, consequently, their ease to be found in other images, strongly depend on the pixel neighborhood intensities. However, in this case, since the points that we are looking for are not the ones with the highest repeatability, understanding the quality of the detection without any data is quite hard. For instance, **Figure 4-19** shows a comparison between the predictions of a random forest trained using BRIEF descriptors and a random forest trained using FREAK descriptors. At a first glance, FREAK seems to be the best one, because it covers the most important areas and it follows the edges of the shapes inside the image. On the other hand, BRIEF avoids some aspects of the image and, moreover, seems to find points with no meaning, like the three points on the top left corner. However, the matchability score obtained with the latter is higher with respect to the former, and this can be explained by looking at the characteristics of the description methods. Indeed, both BRIEF and FREAK extract some information from the intensities of the pixels in the neighborhood

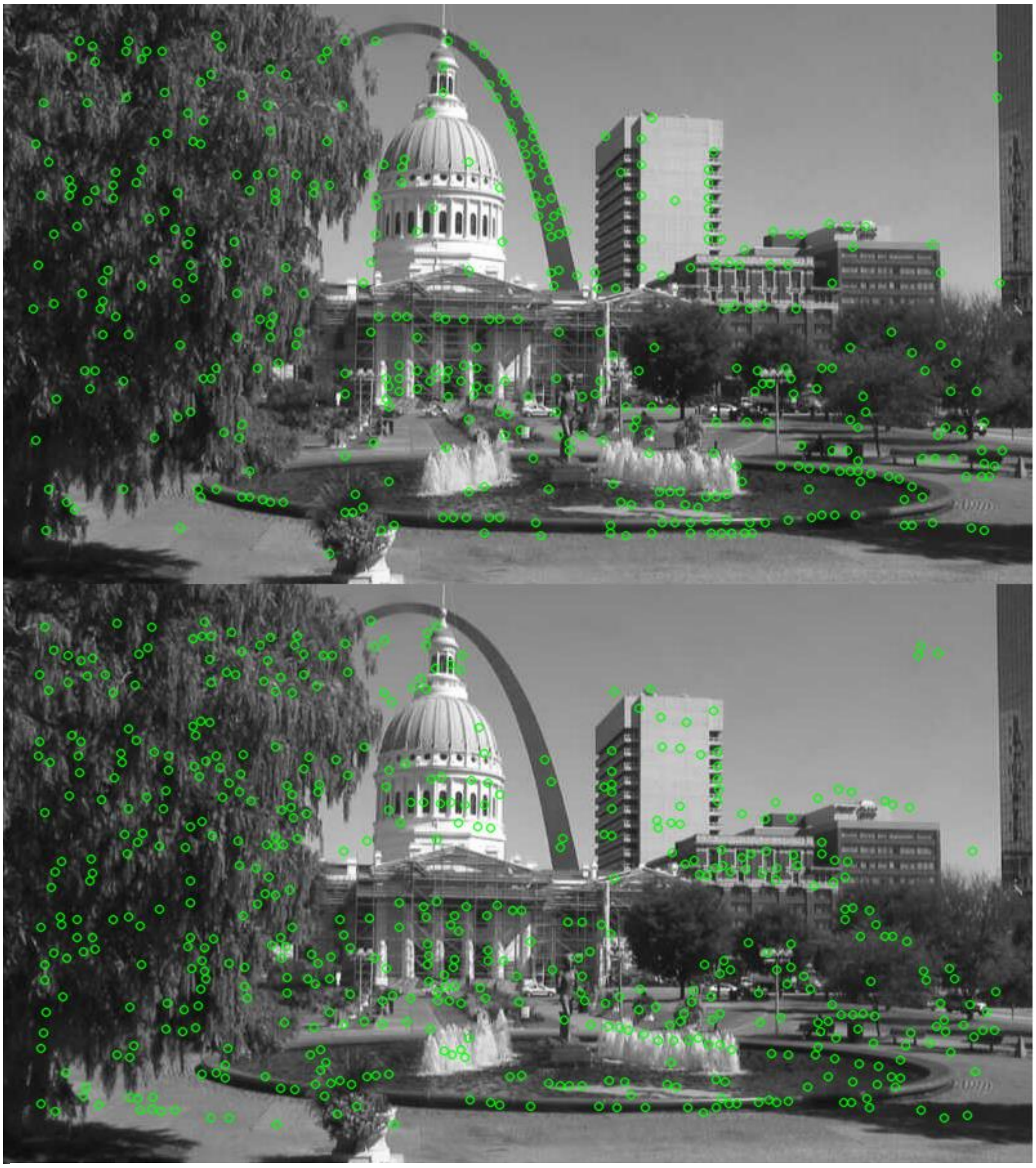
Figure 4-19. Comparison between a random forest prediction using FREAK descriptors (up) and BRIEF descriptors (down)

of the salient point and this can lead to identify a point as positive even if it is not exactly on an edge, but, maybe, near to an edge or to a region that presents a high saliency. It is important to remember that the points we would like to find are the ones that can be found again in a similar image and then, if a point does not belong to an important object or region of the image it does not mean that it could not be an interesting location. As already mentioned, the prediction threshold for a specific dataset has not been fixed yet because, as a consequence, it could be possible to end with no detected points or too many detected points and this would mean a wrong detection in any case. A good solution would be to use the dynamic threshold used during the extraction of the positive and negative samples, but this could lead to very low prediction thresholds, which means keypoints with a bad quality.

Table 4-3. Thresholds and average number of keypoints for every webcam

DATASET	COURBEVOIE		FRANKFURT		MEXICO		PANORAMA		STLOUIS	
DESCRIPTOR METHOD	BRIEF	FREAK	BRIEF	FREAK	BRIEF	FREAK	BRIEF	FREAK	BRIEF	FREAK
THRESHOLD	0.68	0.75	0.7	0.8	0.65	0.7	0.7	0.8	0.7	0.85
AVG #KEYP	275	366	600	478	322	417	414	354	330	240

The average number of keypoints is important because when analyzing the methods through the precision-recall, the total number of points has a strong influence on the final result. It is important to note that in this thesis, the used labels for the random forest are -1 for the negative samples and +1 for the positive samples, thus the threshold can span from -1 to +1. **Figure 4-20** and **Figure 4-21** show the comparison between the precision-recall curve obtained using different predictive threshold over the Courbevoie and StLouis dataset respectively. In the case of Courbevoie, when using the FREAK descriptor, a high value like 0.8 for the predictive threshold penalizes the area under the curve, while a value of 0.75 gives the best result. In the same way,

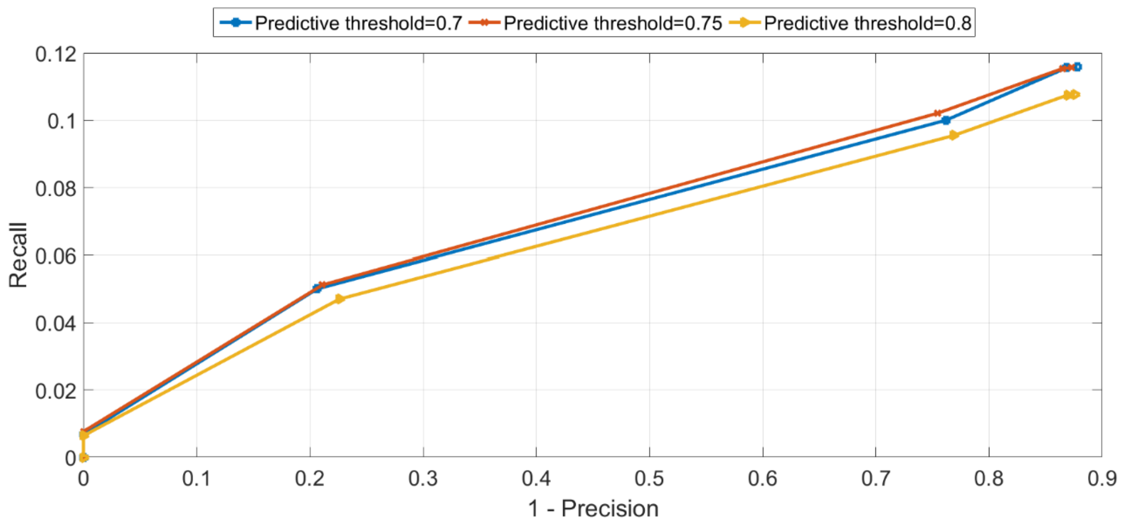

Figure 4-20. Comparison between P-R curves obtained using FREAK descriptor and different predictive thresholds over the Courbevoie dataset

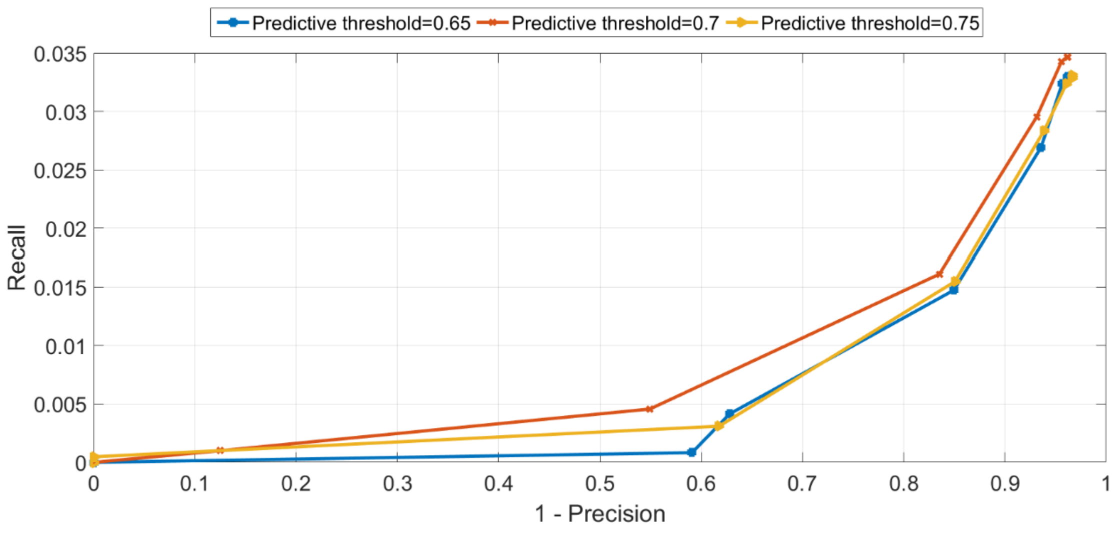

Figure 4-21. Comparison between P-R curves obtained using BRIEF descriptor and different predictive thresholds over the StLouis dataset

the comparison between the predictive thresholds applied to the StLouis dataset shows that a too high value for the threshold penalizes the detection.

Another important aspect is the speed of the detector. When a set of descriptors is fed to the random forest they are analyzed one by one and they are assigned a prediction value that defines their score. If the set of descriptors is big, a lot of time will be required for the forest to process the input and the detection will be slow. Other parameters that influence the speed of the classifier are, for instance, the chosen number of trees and the depth of each tree. In **Table 4-4** are shown the timings of the random forest applied to the test dataset.

Table 4-4. Average speed of the random forest applied to one image of the dataset (note that when using FREAK a sampling rate of 2 is applied to the image)

	COURBEVOIE	FRANKFURT	MEXICO	PANORAMA	STLOUIS
BRIEF	2.7s	8.4s	2.7s	4.3s	2.7s
FREAK	2.6s	7s	2.2s	5.8s	3.9s

The convolutional neural network behaves in a similar way because a prediction threshold must be chosen and the definition of the positive points depend on that value. After the upsampling of the heat-map that the CNN produces, though, a NMS is necessary in order to get rid of all the points that have been added to the image during the upsampling that are not maxima. **Figure 4.20** shows an example of CNN trained over the Chamonix dataset and applied to an image from the

StLouis dataset. At a first glance, the main difference that can be noted with respect to the results from the random forests is that the tree on the left does not contain many positive points, while

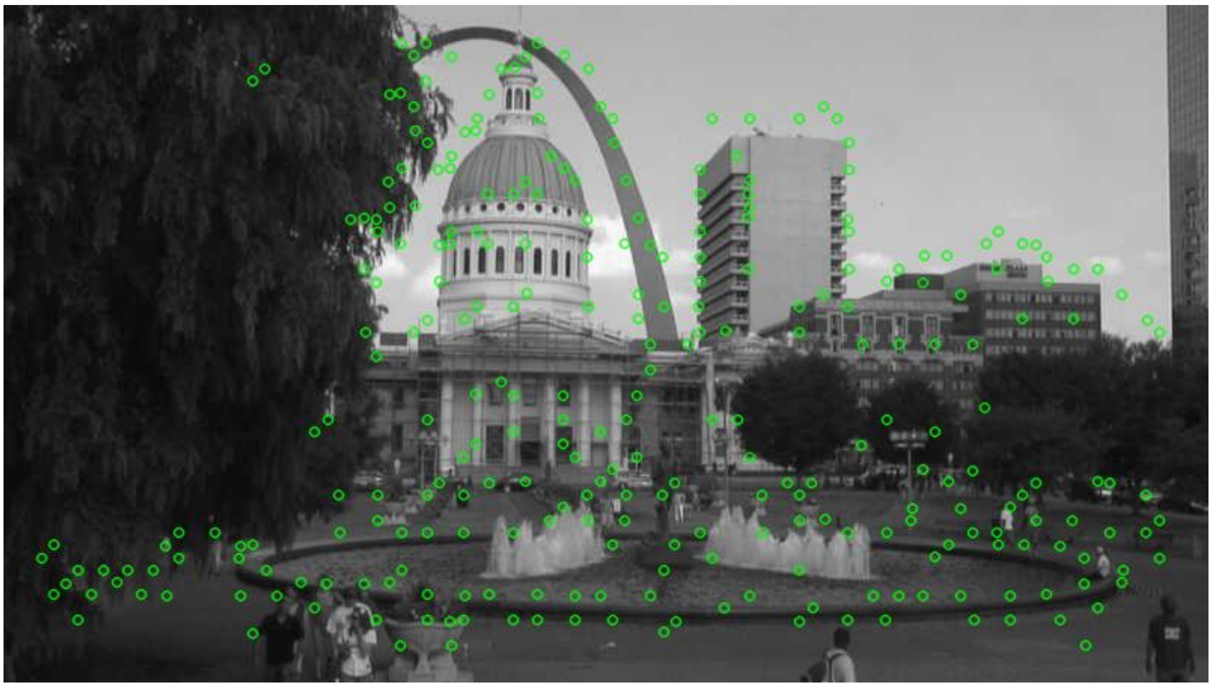
Figure 4-22. CNN classifier applied to an image from the StLouis webcam

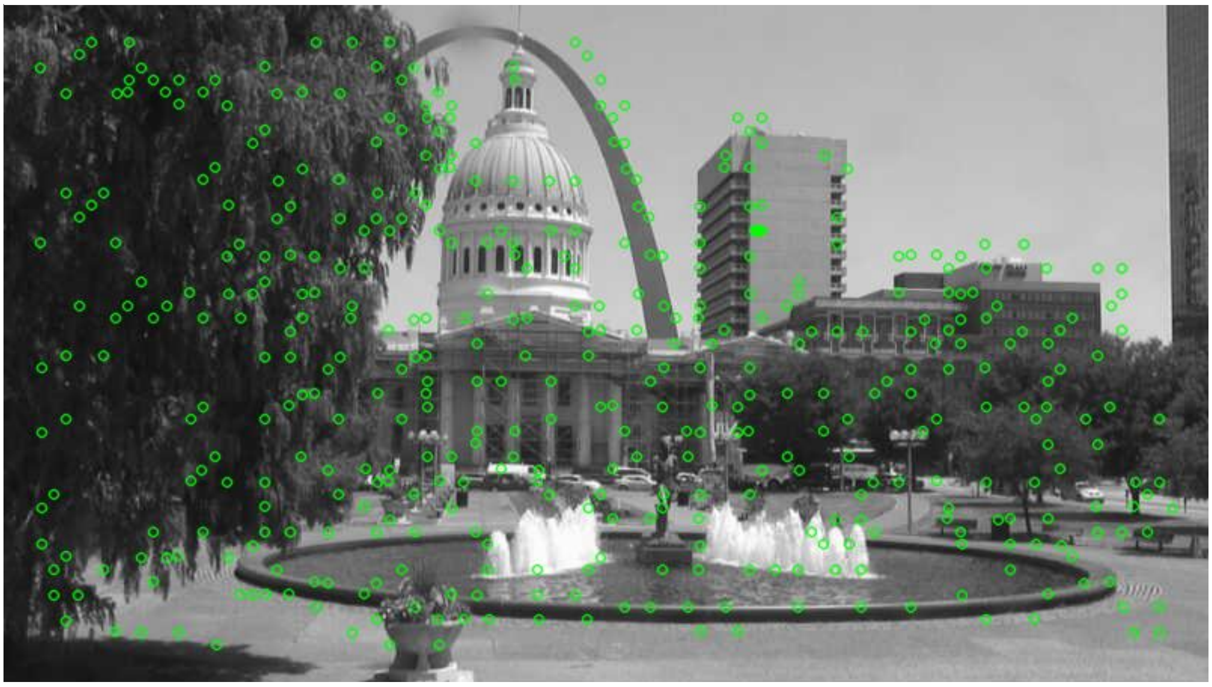
Figure 4-23. CNN classifier applied to an image from the StLouis webcam

as shown in **Figure 4-19**, the random forest identifies a lot of keypoints among the pixels of that tree. This behavior is, probably, a consequence of the way the random forest is trained; indeed, as already mentioned in Chapter 3 when talking about the clouds, training a classifier using a set of descriptors can lead to a wrong classification due to a similar distribution of intensities in those positions where the test of the descriptor is executed. When using patches, instead, this is less likely to happen because the whole intensities distribution of a patch is hardly similar to other intensities distributions inside the image. However, the detection of keypoints in the last case can vary depending on the intensities and this makes the detection algorithm not robust with respect to illumination changes. Indeed, when applying the CNN to the StLouis webcam images, if the tree on the left is very dark few pixels are detected as keypoint, whereas if the tree is clearer the detection is different. **Figure 4-23** shows another example of CNN applied to an image of the StLouis dataset with a strong illumination, where the tree clearly presents many salient points. As a consequence, the results obtained using the precision-recall curve are not so good for the CNN because many points are not consistently detected over the sequence of images. A possible solution to this problem would be a higher number of training samples to be fed to the CNN during the training step. The more the training data the higher the variety of patches to be analyzed by the neural network that will learn, then, more robust weights and biases.

Figure 4-24 shows a comparison between 4 precision-call curves computed using the random forest with both BRIEF and FREAK descriptors and the CNN again with both BRIEF and FREAK descriptors. It is necessary to specify a description method also for the CNN because when computing the curves a matching step is necessary to compare all the images with the first one.

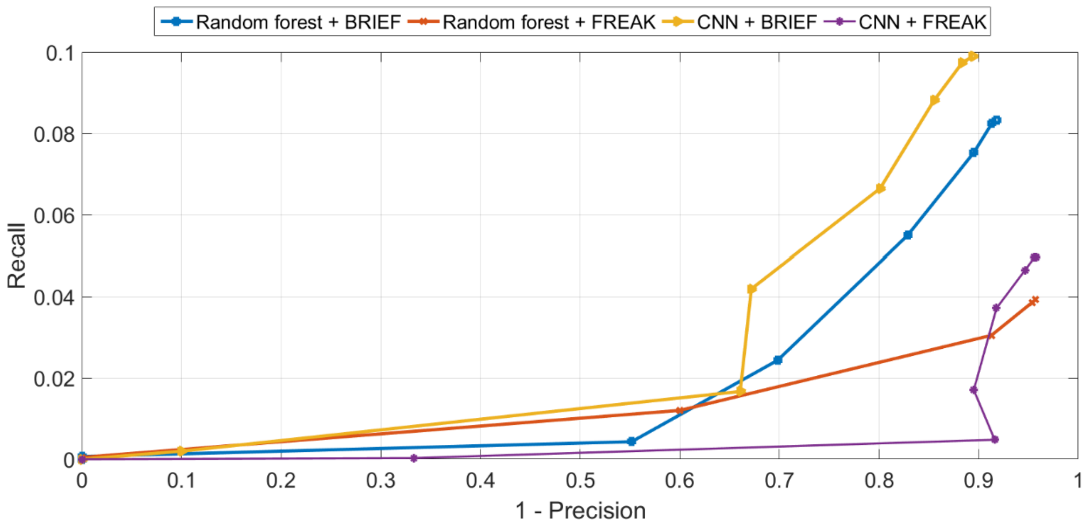

Figure 4-24. Comparisons between random forest and CNN with both BRIEF and FREAK descriptors over the Mexico sequence

The precision-recall curve with the highest area under the curve is the CNN with the BRIEF descriptor, but also the random forest again with BRIEF has a great advantage over the other two curves. In general, the CNN performs better than the random forest, but it is possible to have some misleading results due to an error that occurs when upsampling the image with the bilinear interpolation. Indeed, some new points that have a prediction value inferred by looking at the neighborhood, could have an equal score and this can lead to a detection that is too dense in specific areas. Since when building the precision-recall curves a matching error is considered, if many points are too near is easy to get a higher result. A solution to this problem could be a non-maxima suppression, but since all the points have the same prediction, the only result would be to keep them all or to discard them. In this thesis those points are kept.

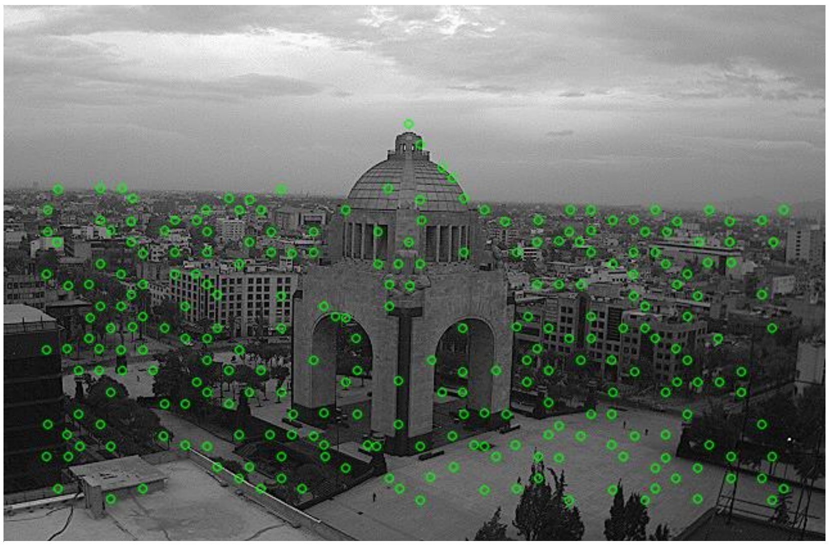
Figure 4-25. CNN keypoint detection over an image from the Mexico sequence

This phenomenon can happen with some test images, but it is not always the case; indeed, **Figure 4-25** and **Figure 4-26** show that when applying the network to the Mexico sequence this problem is not present, while when dealing with the Courbevoie dataset it is possible to have it.

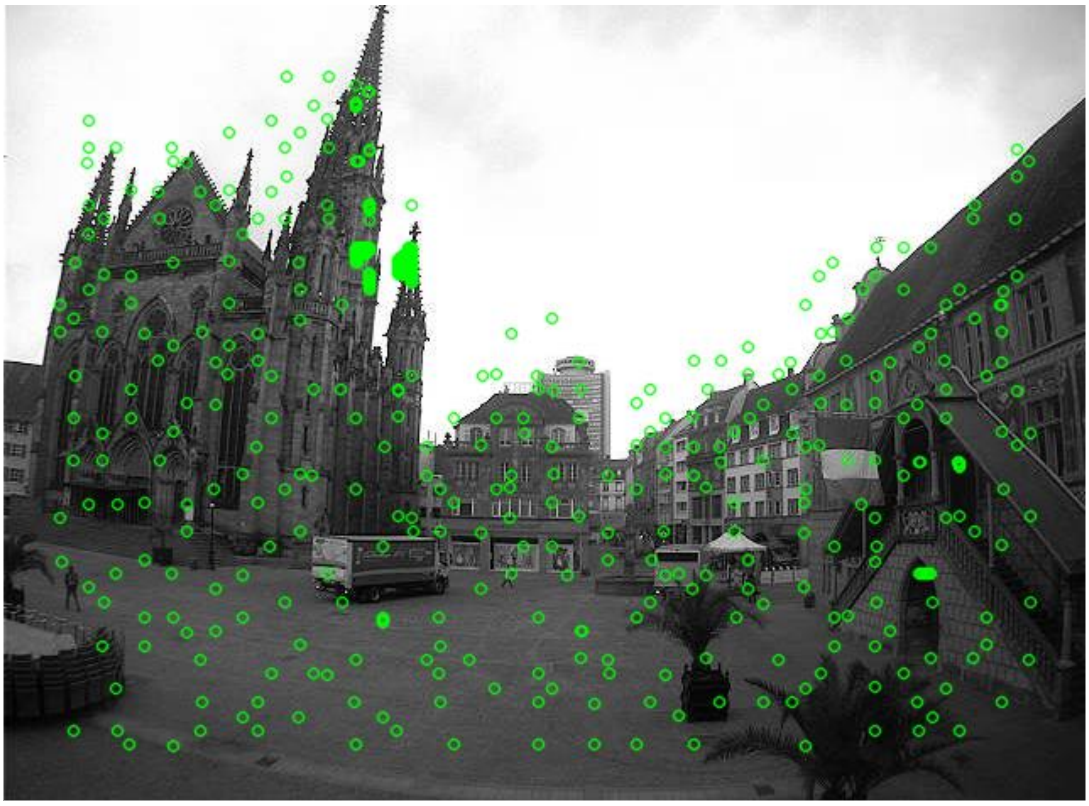
Figure 4-26.CNN keypoint detection over an image from the Courbevoie sequence

4.4 Comparison with TILDE

"Temporally Invariant Learned DEtector" uses a different approach for both the extraction of the positive locations and for the classification. However, the general idea is the same, i.e. building a keypoint detector using a trained classification algorithm. One of the most important differences

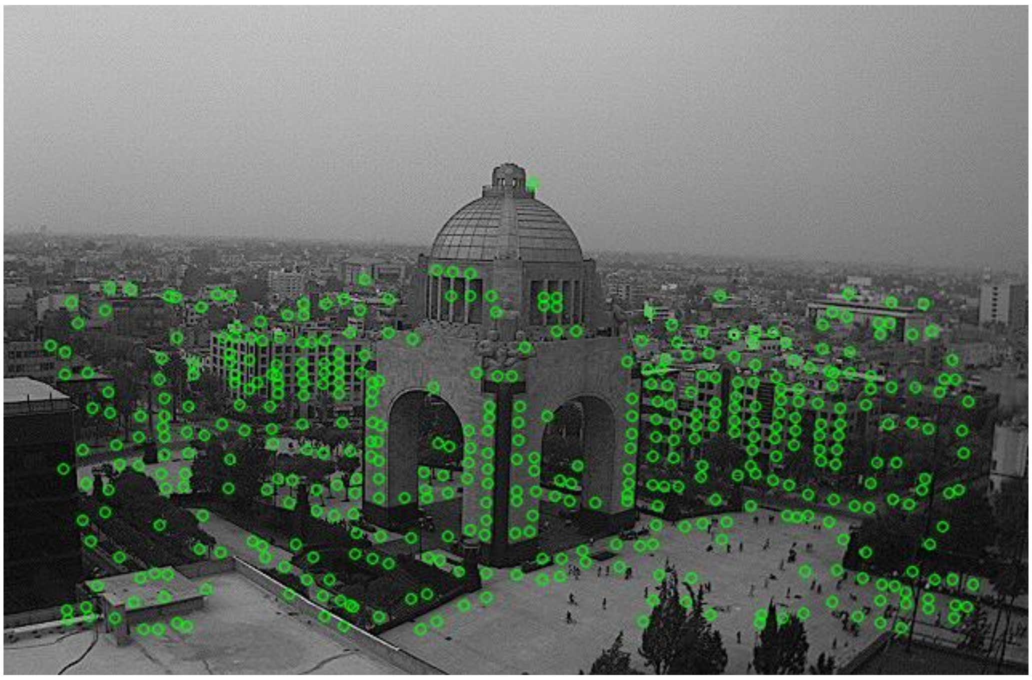

Figure 4-27. Keypoint detection using TILDE on an image from the Mexico sequence

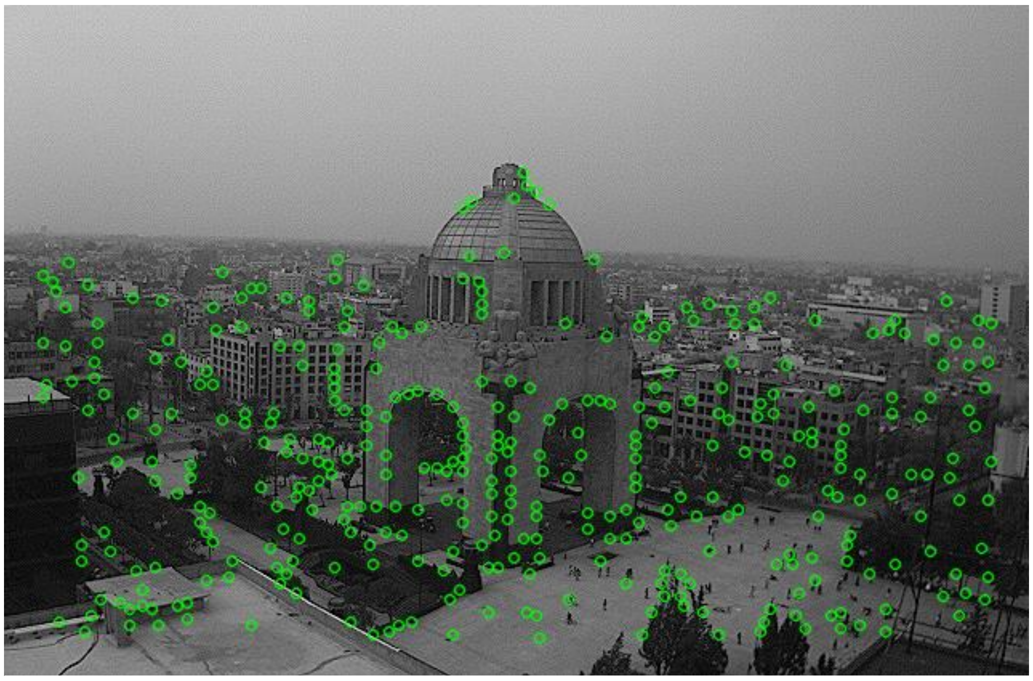

Figure 4-28. Keypoint detection using the random forest on an image from the Mexico sequence

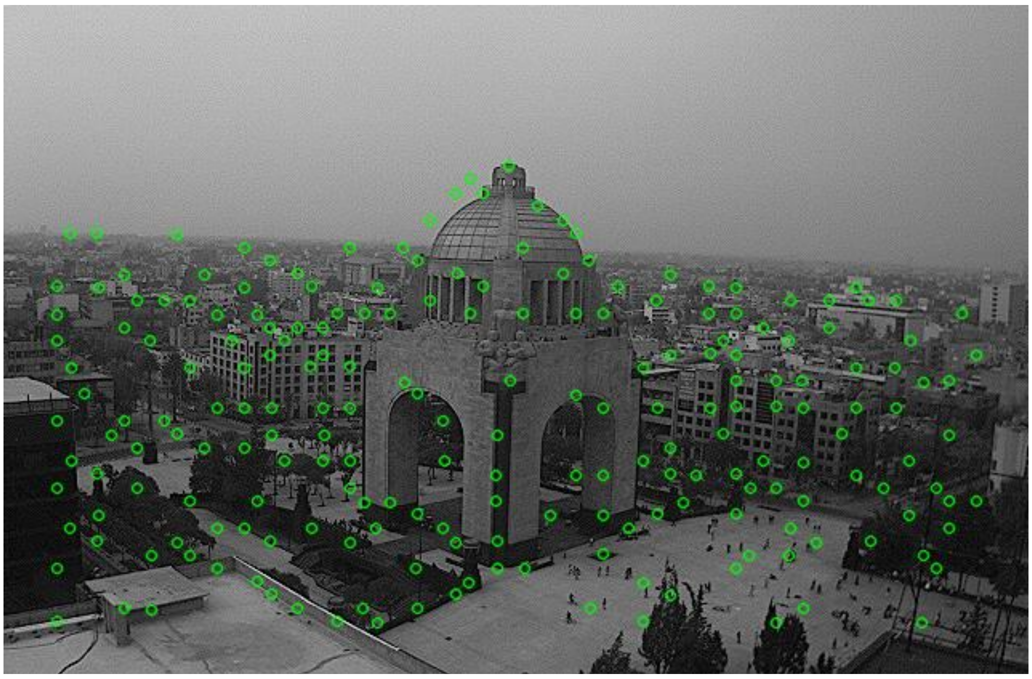

Figure 4-29. Keypoint detection using the CNN on an image from the Mexico sequence

between TILDE and the method developed in this thesis is that TILDE detect always almost 500 keypoints, while, with the random forest used here, the number of detected keypoints depends on the threshold that is chosen. The few number of keypoints detected using the CNN is probably due to the fact that too few training images have been used in this work, and this leads to values of the predictions that are too low.

Figure 4-30 shows a comparison between the precision-recall curves obtained using the random forest, the neural network and the method proposed in TILDE, all applied to the Courbevoie

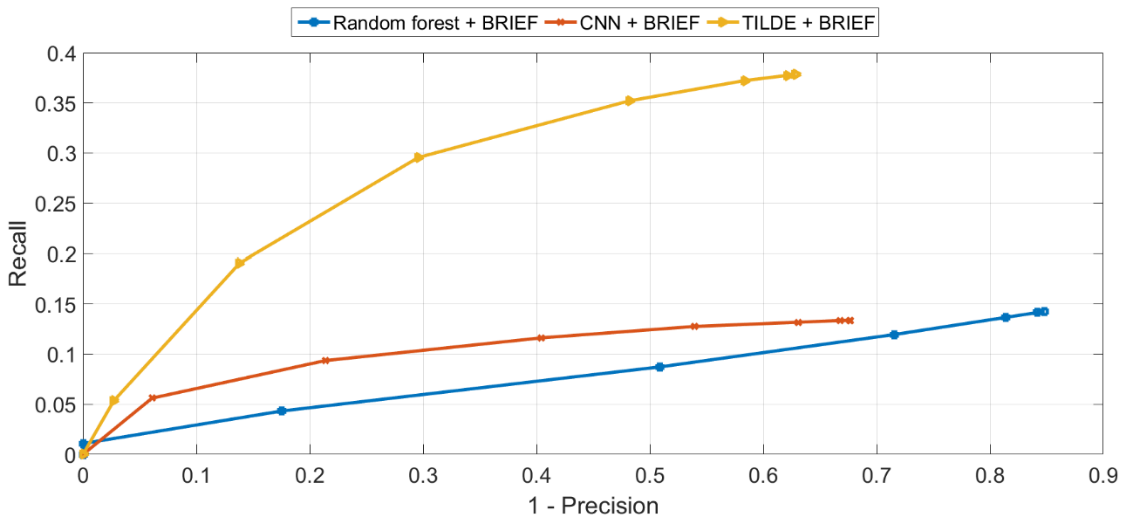

Figure 4-30. Comparisons between random forest, CNN and TILDE using BRIEF descriptor over the Courbevoie sequence

sequence. It is easy to see that TILDE (only the best result that TILDE can obtain between the "normal" approach and the fast one is considered here) outperforms the other two methods with

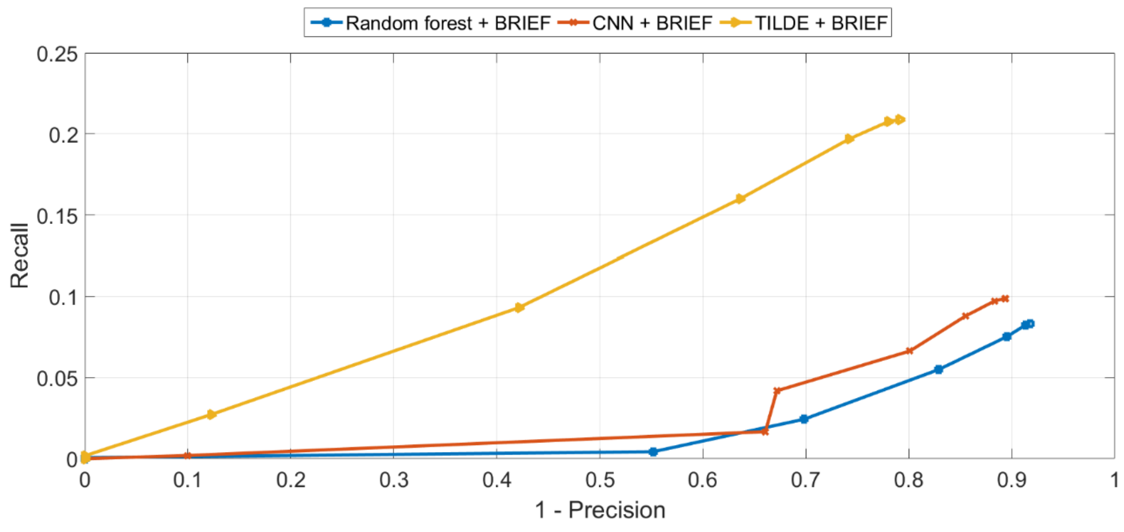

Figure 4-31. Comparisons between random forest, CNN and TILDE using BRIEF descriptor over the Mexico sequence

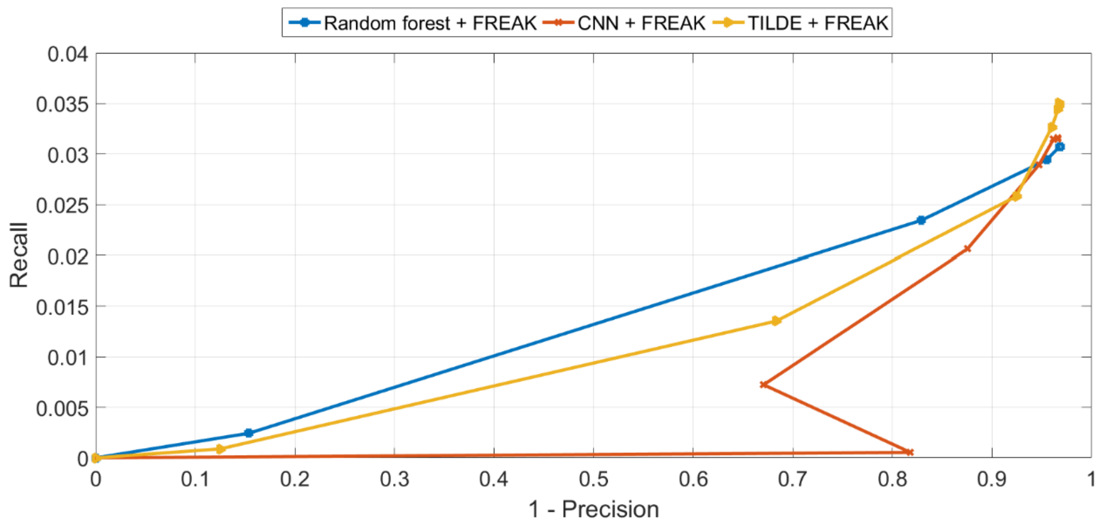

Figure 4-32. Comparisons between random forest, CNN and TILDE using BRIEF descriptor over the StLouis sequence

a final value of 0.37 for the recall and an AUC equal to 0.17. **Figure 4-31** and **Figure 4-32** show the results from two others webcam sequences, namely Mexico and StLouis. In the case of Mexico, the result is quite similar to the previous one, with a good performance from TILDE and worse performances from the other two methods. When analyzing the StLouis sequence, instead, the Random forest slightly outperforms TILDE with an AUC of 0.013 against 0.010. However, the scores obtained over such dataset are quite small and, then, the difference is not so remarkable.

CHAPTER 5
CONCLUSIONS AND FUTURE WORK

This work presented a machine learning approach for the first step of the detection-description-matching pipeline, a common paradigm for many computer vision applications. The state of the art of keypoint detection is composed by many algorithms that have been created and optimized in order to find specific shapes and to detect keypoints that present a very high repeatability. However, this does not guarantee that the salient points will be the optimal ones during the successive matching step. In this thesis, an innovative approach has been developed for the keypoint detection, with the purpose of maximizing the matchability of the detected keypoint. The idea behind this work comes from "Learning a Descriptor-specific 3D Keypoint Detector" [9], a paper in which the authors used a random forest classifier to detect points in 3D objects. However, this thesis focused on the 2D case instead of the 3D and requires, then, an a priori definition of the transformations the detector should be invariant to. In the 3D case the transformations were 3D viewpoint changes, while here they consist of illumination changes due to drastic weather variations.

The classifiers used in this work were a random forest and a convolutional neural network, both trained after the definition of the positive and negative locations from which the training samples are extracted. These positive and negative locations are the coordinates of the points that give correct correspondences during a first matching step and the descriptors extracted at each one of these points compose the set of training data for the random forest. The neural network, instead, does not require any feature to be defined a priori because the salient information is extracted autonomously from the patches that are used for the training of the network. After the training of the classifiers, a validation of the parameters, such as the sampling rate of the training images, the number of trees to be used in the forest, the learning rate of the neural network and some others, has been done. During the final testing step, some possible configurations of parameters, like the description method or the predictive threshold of the random forest, have been tested on unseen input images undergoing the same type of transformation, i.e. illumination changes, and compared to each other. In the last part of Chapter 4, the results obtained using the methods developed in this thesis have been compared to the performances of the detector developed in [6], in which a similar approach to the keypoint detection has been studied.

The gap of performances between TILDE and the two methods proposed in this work could be filled with some expedients. For instance, it is possible to consider other transformations in addition to the already considered illumination changes like, for example, rotation, translation and scale. The positive and negative samples that are robust to such transformations can be used for the extraction of the descriptors for the training of the random forest and for the extraction of the patches to be used with the neural network. Regarding the CNN, a larger training dataset would make the network more robust and more capable of finding keypoints. The only problem with larger dataset is that it would be necessary to add samples to the already existing one that are perfectly aligned or, otherwise, to align every image to the previous ones before the extraction of the samples. It is also possible to train a different and more complex convolutional neural network in order to better infer the weights and the biases. Finally, a possible solution to the cluster of points with equal prediction values would be the definition of a function that can extract a single point or some points from the clusters, for example by looking at the geometry of such clusters. All these possible improvements are left to future investigations.

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