Image analysis methods for localization of visual codes

Theses of PhD Dissertation

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1 Introduction

The application of computer-readable visual codes has become common in our everyday lives. Their importance has increased not only within industrial environment, but in private use as well [15]. Computer-readable visual codes are universal, and their production is less expensive than using other technologies, such as radio frequency identification (RFID) [13]. They provide simple and reliable identification of items at postal services, point of sale (PoS) terminals, and warehouses of various products. The availability of codes using desktop printers, and penetration of automatic checkout systems at supermarkets [25] also greatly contributed to the popularity of these codes.

We have to take two steps to regain the data embedded in the visual code, namely, localization and data decoding. In the first step, the presence of the barcode, and the location of the barcode to the sensor has to be recognized. In most cases, we also apply transformations, like noise reduction, sharpening, normalization, and correction of distortions. After this step, the processed image piece containing the code is passed to the detector that looks up the pattern for valid character data.

When proper localization and pre-processing is applied, then the latter step is relatively straightforward since characters are easily recognizable thanks to the maximized hamming-distances between entities. In addition, most bar code standards also provide redundant information for error correction purposes. Localization step has more difficulties due to the variety of code types, cameras and scenes.

In the early age of barcodes, localization was manual. A data terminal or a portable barcode scanner was positioned and oriented against the item having the code object, in order to recognize it. Barcode reading on recent smartphones is still at this stage.

Since the past couple of years, image acquisition techniques and computer hardware have also improved significantly, automatic reading of visual codes became available [36], however, it raised the localization problem to the next level of difficulty. Visual codes have to be reliably found without human assistance, based on the sensor data. Each application has its properties, like, the expected type of barcode, type of the sensor, and constraints of size, orientation, and number of codes present within the observed area. After the successful localization of the code, the decoding step follows, which means retrieval of the embedded data by the software. While the localization step became more complex due to the expectation of automatism, the reliability of decoding can be contributed to the availability of more accurate sensory data and additional computational capacity.

As applications impose special problems, there is a continuous need for solutions with improved effectiveness. There are several methods for barcode localization that are characterized by the processing techniques they use, accuracy and speed. However, state of the art algorithms, while giving efficient methods to the decoding step, still lack universal solutions for localization. This implies the need of research in that step of the reading process. The primary objective of this thesis is to examine and improve existing algorithms for barcode localization, and to design new ones. Recent trends in computational capacity also allow using machine learning approaches and classifiers based on more complex features [3,30] than the ones used at barcode scanner devices.

Barcode localization methods have two objectives, *speed* and *accuracy*. For industrial environment, accuracy is crucial since undetected (missed) codes may lead to loss of profit. Processing speed is a secondary desired property of the detectors. On smartphones, accuracy is not so critical, since the device interacts with the user and re-shooting is easily done, nevertheless, fast (and reasonably accurate) barcode detection is desirable.

2 Results of the dissertation

2.1 Simple algorithms based on global information

In this section, methods are presented that use features based on global information, which means all sensor data is available for the algorithm at the same time. The very first idea was the scan-line analysis, that came from the early age of computer vision, where mathematical morphology [29] was too time-consuming to perform on high resolutions. However, the spreading of embedded systems renewed the interest of these simple algorithms, and gave motivation to improve existing algorithms and develop new ones. Moreover, these algorithms can be designed, verified and fine-tuned more easily than machine learning approaches.

There is a wide selection of papers on scan-line analysis [16, 31, 32], having the same simple idea. Scanned lines form 1D intensity profiles (Fig. 1(b) and (c)). Barcode detector algorithms [1, 22, 32] work on these profiles to find an ideal binary function that represents the original encoded data. The main idea is to find peak locations in blurry barcode models, then thresholding the intensity profile adaptively to produce binary values.

Although scan-line based solutions are fast, they have low tolerance to noise and smoothing. I examined the scan-line method and evaluated possible modifications. I introduced scan-line analysis for 3 and 4 directions, and instead of density images, proposed grouping of line segments using endpoint and proximity conditions (Fig. 2).

Methods involving mathematical morphology use operations derived from erosion and dilation [21,23,27]. This group of algorithms has the common properties of larger computational cost and higher level of robustness. I also proposed an algorithm involving morphology [9], that uses morphological gradient, opening and contour detection. Its steps are summarized in Fig. 3.

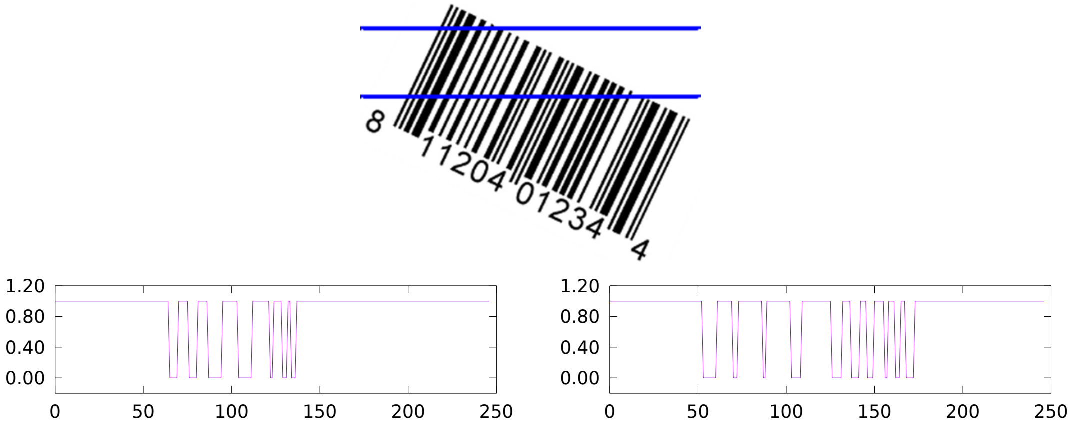


Figure 1: The idea of scan-line analysis. Scan-lines sweep through the code, finding areas with frequent intensity changes (ROI). ROI endpoints are also barcode contour points. Each scan-line makes an 1D intensity profile.

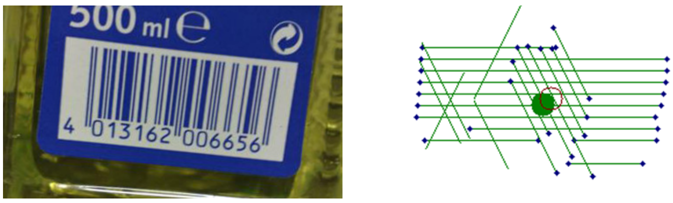


Figure 2: Scan-line analysis of real-life example. Original image (left) and the feature image (right), with line segments, endpoints, center for the horizontal line group (green, filled disc), and center for the 60° line segment group (red circle), dropped due to proximity to existing center point.

Additionally, one shall not forget to mention the existence of algorithms that involve Hough transformation [2, 24, 35], which results in a set of line segments, that can be further processed [34]. I introduced and evaluated the capabilities of Hough transformation for barcode localization in images.

2.2 Algorithms using image tessellation

End-user applications mostly have limited resources, like memory and processing power. Not all hardware setups let to store the whole image in memory, some even drop information as new sensory data is acquired, thus providing only partial data by time.

Image tessellation (partitioning the image to uniform cells) is a wide-spread idea of pattern recognition, which can be used as the base of barcode localization. This approach is applicable because most barcodes, just like areas covered with textures, can be easily identified by observing only small parts of them. These barcode parts together form the desired barcode region with known height and width.

I presented methods that work with image tesselation and make decisions based

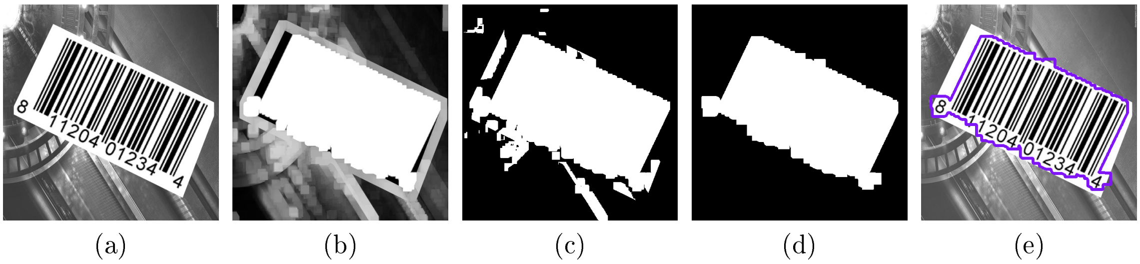


Figure 3: Stages of MIN–MAX method. (a): original image; (b): morph. gradient; (c): binary threshold; (d): opening; (e): contour overlaid to original image.

on local cell information [6, 9, 20]. The algorithm family performs localization by partitioning the image into square cells and by recognizing each cell as a barcode piece.

It is important to note that each cell is assigned a value that indicates the grade of the barcode presence, however, the choice of the feature varies. As the result of the evaluation, a matrix is formed from these values, each element representing a cell value. Barcode parts have similar local statistics in their neighborhood, hence, searching this matrix for compact areas of similar values defines regions of interest, representing barcodes with high certainty. Furthermore, it is important to mention the compactness of code parts, which attribute helps to filter out small cell groups or groups having low compactness.

Replacing the classical line-scanning method is one of the improvements I proposed in this section, published in [11]. The modification of the scan-line approach with circular pattern involves the subsequent procedure. As the beginning, it is required to convert the image to binary by thresholding. Binary images are divided into square tiles with overlapping by half the tile size. Each tile is processed individually at first, and a measure is assigned by evaluating pixels in a circular pattern, with the tile size as diameter. A one-dimensional profile is obtained, which has zero-crossings of various densities.

After this step, the circle forming the intensity profile is divided into four equal-sized quadrants by density of zero-crossings. Image parts representing a barcode have equally low or high number of crossings at opposite quadrants, and significant difference in the number of crossings at neighboring quadrants. For the sake of simplicity, quadrants having many and few zero crossings are labeled as “Wild” and “Calm”, respectively. Those quadrants can be defined and separated, as shown in Fig. 4.

Runlength Measuring is a tile-based local scan-line approach. It requires using a well-chosen tile size, each tile is examined using two pairs of perpendicular scan-lines, one pair at 0° and 90° and the other at 45° and 135° (Fig. 5). A measure is derived from the difference of the count of the intensity changes along the scan-lines. For instance, a horizontally aligned barcode has a lot of intensity changes when scanned

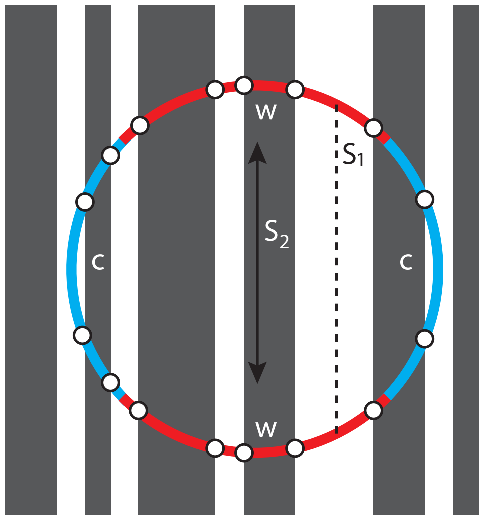


Figure 4: Zones and symmetries of the circular intensity profile. Wild (w) and calm (c) zones, symmetry at pixel level (S_1) and between quadrants S_2.

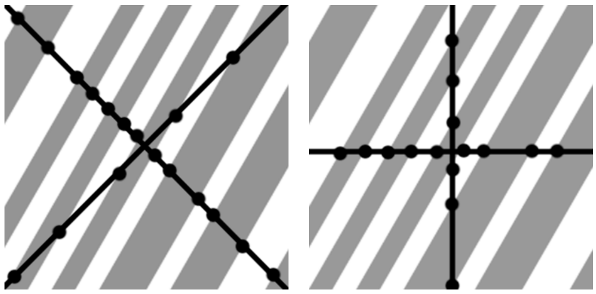


Figure 5: Two pairs of scan-lines sweep through the image. One of them has significantly higher number of zero-crossings in case of positive response. In this example, the barcode is fully recognized by the first pair of scan-lines.

with a horizontal scan-line, but has few or none with a vertical (Fig. 5).

With the 2 pairs of scan-lines, barcode pieces of any orientation can be safely recognized. The final measure assigned to a tile is the maximum of the two differences. This measure gives 1 if parallel lines are present on an image tile, and 0 if a tile contains a homogeneous area, or noise.

Local pixel clustering [9] is the most simplistic algorithm based on image tiling. It divides cells into black and white segments. An image region that contains a barcode part has many similar stretched clusters.

I also propose an algorithm for localization based solely on distance transformation [14]. It can be used individually with limited performance, or as an intermediate filtering step for creating more sophisticated algorithms.

Furthermore, I introduced a new algorithm based on cell histograms. In case of an ideal cell containing a part of a visual code, only black and white intensities are present cell-wise in roughly 1:1 proportion. Due to the variability of the code object

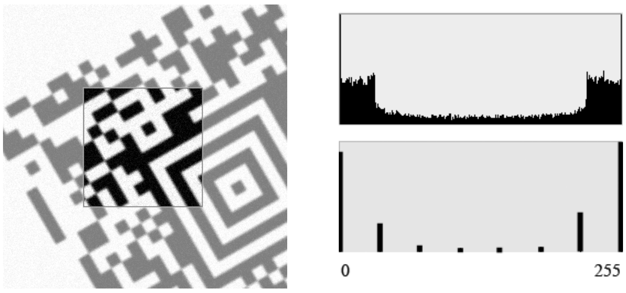


Figure 6: Aztec code part with 25 % uniform noise and Gaussian blur ($\sigma = 2$) (left), its 256-bin histogram (top-right), and 8-bin histogram (bottom-right).

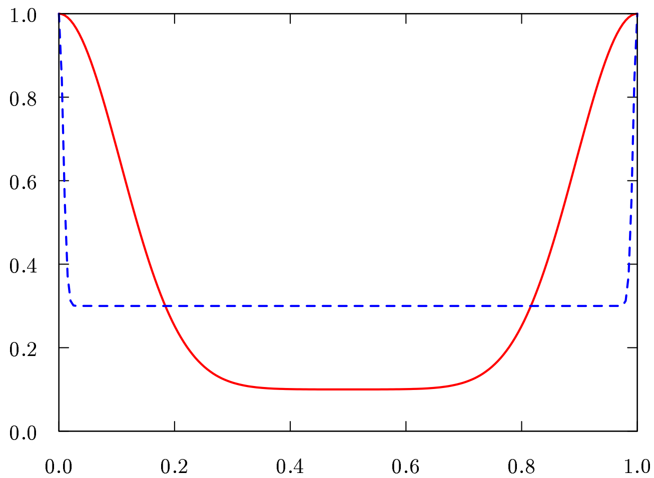


Figure 7: Expected probability functions. Red solid curve: small C (expected smoothing) with moderate amount of expected noise $C = 0.1$, $\sigma = 0.15$ (example for dirty environment), blue dashed curve: larger C with smaller amount of expected noise $C = 0.3$, $\sigma = 0.01$ (example for low quality phone camera).

and imperfections of image acquisition devices, the intensity histogram deviates from this ideal case (Fig. 6). To take the effects of image acquisition flaws, a formula can be introduced to model theoretical cell histograms as

$$U_{C,\sigma}(x) = C + (1 - C)\left(e^{-\frac{x^2}{(\varepsilon+\sigma)^2}} + e^{-\frac{(1-x)^2}{(\varepsilon+\sigma)^2}}\right), \tag{1}$$

where C and σ are set according to the level of noise and smoothing, respectively. Different values of σ and C lead to different distributions (Fig. 7).

Speed is a primary or secondary objective in most cases. Algorithms of this chapter use simple features and thanks to the local measurements, they can be parallelized easily.

Simple detectors can be aggregated in many ways, such as, majority voting, using the maximum value of all, or weighted voting [5]. Each approach is appropriate for fulfilling different goals. Majority voting can be applied with good results when the single detectors have relatively low precision with a moderate or high recall rate. In this thesis pixels with higher certainty are classified in this way, while keeping false positives at low rate. Using the maximum value of the feature images produced by the individual detectors is good for maximizing the recall, for example, detecting all possible ROIs, but it dramatically decreases precision when the single detectors are weak on that property. However, we can use that approach in industrial setups, where detecting all barcode locations is of crucial importance. One can also experiment with weighted sum of the feature images.

2.3 Neural networks for the localization task

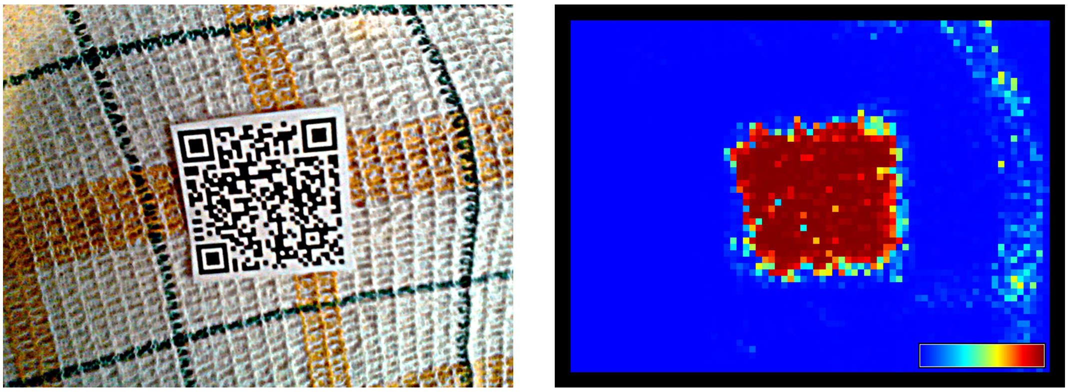
Both 1D and 2D visual codes have high variability regarding element layout. It would be problematic to manually enumerate all configurations or to construct features that give positive response to all of those configurations. However, with neural networks, learning the layout can be automatic and definition of patterns is not necessary.

During the last few years, there has been a renewed interest in applying neural networks, especially deep neural networks, for various tasks. As their name suggests, deep neural networks (DNN) differ from conventional ones (ANN) in that they consist of several hidden layers. However, if we want to train these deep networks properly, we have to be aware of the fact that the training method requires modifications as the conventional back-propagation algorithm encounters difficulties, like the so-called "vanishing gradient" and the "explaining away" effects.

Similarly to the presented methods based on image tessellation, the input vectors of the neural network are formed on block level. For each block, the neural network assigns a measure which reflects the probability of presence of a QR code part in that block, resulting in the feature matrix (feature image), that represents regions of interest (Fig. 8). The next step of the process is to find clusters in this matrix that have sufficient size, compactness and high values of probability to form a QR code. The final step is the same as the one for previously presented approaches. More precisely, the cluster centers that satisfy the above conditions are returned, and the bounding boxes for the QR code area candidates are given.

JPEG [33] is one of the most common still image formats, and provides efficient data storage and transfer. Most cameras can acquire images directly to JPEG format, and some devices can even output a stream of JPEG images, which motivates research into image processing methods using this format.

Neural networks are also capable of learning in the frequency domain, and JPEG format can be handled as a subset of that domain, also having fixed 8×8 px block size for input. For this case, one of the deep rectifier networks proposed in this thesis works directly with the DCT coefficients of the JPEG image. Using this approach, only the first steps of the decompression have to be performed for code localization, while the most complex step, inverse DCT can be skipped.



(a) example real-life image (b) feature image

Figure 8: Image captured by a phone camera and visualized feature image according to the output of the neural network.

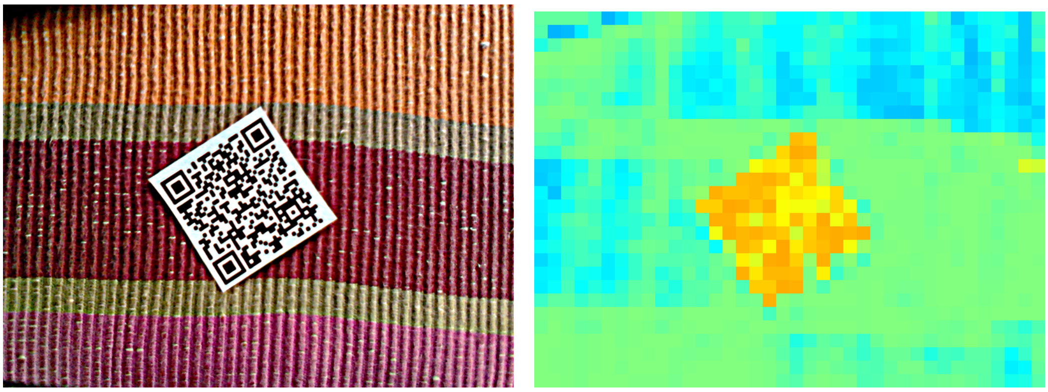
2.4 Boosted cascade of weak classifiers

Belussi et al. [3] experimented with classifiers based on Haar-like feautres, and proposed parameters for visual code localization. Their classifier was trained on the Finder Pattern (FIP) of the code object. According to their experiments, the most accurate classifier uses only the basic set of wavelets, weak classifiers are organized into cascade topology with a maximum 1 split, each having 50 % false positive rate and 4000 samples of 16×16 px size.

Instead of Haar-like features, Local Binary Patterns (LBP) and Histograms of Oriented Gradients (HOG) can also be used for the feature evaluation. The concept of partitioning of the image, and reading each block in the aforementioned circular pattern, is analogous to LBP [28], with the main difference of not using the center point for making the feature.

In order to increase the strong features of the object intended to detect, this thesis proposes training of a classifier for the whole code area. Even though QR codes have high variability on the data region, they contain data density patterns, a fourth, smaller FIP that can be perfectly covered with the center-type Haar-feature, furthermore, they contain the three discussed FIPs at the corners of the code.

LBP and HOG based classifiers can also be trained both to FIPs and whole code areas [11], and since they are also considered fast and accurate general purpose object detectors, evaluation of their performance on code localization is highly motivated. Moreover, LBP is more suitable than Haar classifiers, since it is not restricted to a pre-selected set of patterns, while HOG is also efficient due to the strict visual structure and limited number of distinct gradient directions of the QR code.



(a) (b)

Figure 9: Printed QR code on tablecloth (a) and its FIS feature image (b).

2.5 Fuzzy Inference Systems

A simple approach to identify textures is using various stochastic measures [18], while Wang [19] introduced a more sophisticated texture filtering algorithm using *Texture Spectrum* as a general measure for texture properties, and *Texture Units* that express local intensity relations within an image cell. Lee et al. [26] even introduced the *Fuzzy Uncertainty Texture Spectrum* and *Fuzzy Texture Units*, a more generalized way of texture identification involving evolutionary algorithms and fuzzy logic. However, the computation of these features would take a notable amount of time on embedded systems and make on-line processing very hard to implement. Instead, terms of fuzzy theory can be applied in order to detect barcodes and Fuzzy Inference Systems (FIS) can perform evaluation rapidly, regarding the features they use.

The use of fuzzy algorithms are already proven to be efficient for QR code localization [37]. I propose a Fuzzy Inference System (FIS) based on the most simplistic, attentive features of a QR code, but this approach can be adapted to all 2D code types mentioned above [8].

The algorithm is efficient with respect to computation time and storage, and most of the computed features can be approximated using only a subset of pixels, that allows fine-tuning of the application to be faster or more accurate. These properties can make FIS-based localization a preferred choice over other fast algorithms.

The proposed FIS consists of three input and one output variables. Membership function (MF) parameters are tuned each time to the end-user setup using statistics of a few input images. For the selection of properties, simple features that represent humanly observable properties are pursued. The three properties that can be summarized in the following statement: QR code parts consist of mostly black and white pixels of similar amounts, while having from moderate to high contrast and low saturation.

The feature set is extensible. For cases where the aforementioned principles do not have the required classification power, runlength measuring can also be used together with the basic rule set.

3 Summary of the thesis points

1. I introduced 3 new algorithms for barcode localization in image using global information. These, respectively, are based on scan-line analysis with new features, Hough transformation, and mathematical morphology operations. The latter two outperform state-of-the-art algorithms in terms of accuracy and recall, while the scan-line approach is very fast and is also reasonably accurate.

2. I proposed new algorithms for the localization of visual codes using the idea of image tessellation. The proposed algorithms have low computational and storage requirements, and can be easily adapted for parallel computation.

   2.1. I proposed cell histograms, distance transformation and a modified scan-line approach for local feature formation. I have also shown that an ensemble of simple detectors can have higher precision or recall than state-of-the-art algorithms, depending on the type of aggregation and involved features.

   2.2. I implemented a rotation-invariant feature adapted from the scan-line approach. The new feature uses local intensity profiles read along a circular pattern, and takes advantage of symmetries and neighboring cell information.

3. I introduced and evaluated neural networks for visual code localization in images.

   3.1. Through the experiments I have shown that the use of Deep Rectifier Networks is a viable option for barcode localization, both in image space and in the frequency domain, even with binary images.

   3.2. I have also shown that Deep Rectifier Networks can be trained on JPEG DCT vectors, that eliminates the need of the inverse DCT step of the JPEG decoding process.

4. I evaluated the performance of cascade classifiers and their usability for barcode localization, and proposed new extensions.

   4.1. I proposed 2 new features for the training, namely, Local Binary Patterns (LBP) and Histograms of Oriented Gradients (HOG). They are proven to be more accurate compared to Haar-wavelets, which is presented in cascade classifiers from the state-of-the-art.

4.2. I proposed learning on the full code object instead of learning on the finder patterns exclusively, which greatly simplified post-processing.

5. I introduced Fuzzy Inference Systems for barcode localization, that provides fast execution and a flexible model construction.

Publications by the author, related to theses

Publication	Thesis point							Type
	1	2.1	2.2	3.1	3.2	4	5	
[9]	•	•						conference paper
[5]		•						conference paper
[6]		•						conference paper
[11]			•					conference paper
[10]	•	•	•					journal paper
[17]				•				conference paper
[4]				•	•			conference paper
[7]						•		conference paper
[8]							•	conference paper
[12]						•		journal paper

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