Research of Classification Algorithms for Recognition of Digits in Mechanical Counters

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Abstract: Mechanical counters are still very popular for their protection against manipulation and low costs. In the past automatic readout of mechanical counters required complex and expensive image processing methods. The system proposed in this paper is a cheaper alternative which does not require modifications to the mechanics of the counter. The proposed system makes use of different light reflectivity parameters of the numbers shown on the number wheels. In this paper the different approaches are shown and analyzed.

1 INTRODUCTION

Presently mechanical counters are very common when a high degree of protection against manipulation is required such as in counters for water, gas or electricity consumption. Furthermore mechanical counters are commonly used in cash and gaming machines. Since the costs are very high if persons have to read out the counter value manually, methods for automation of this process were developed in the past years.

2 STATE OF ART

One system uses an electronic counter which has to be fitted to the mechanical one. Unfortunately this does not read out the actual value of the counter which lessens the protection against manipulation.

There are different methods for the evaluation of the optically sampled counter value. The method proposed in this paper makes use of a pattern recognition in gray scale values. It was described in (Benyoucef et al., 2012). The emphasis of the paper (Benyoucef et al., 2012) was on external influences such as scattered light or temperature drifts. In contrast this paper concentrates on the pattern recognition and enhancements of the method.

Additionally other references committed to the readout task are discussed in the following. As an example Otsu proposed an evaluation method which analyzed the resulting histograms of several images (Otsu, 1979). A similar application is shown in (Martinez-Carballido et al., 2011). In (Qian et al., 2006) tried to detect the figures on banknotes. The correct mapping of the measured gray values to the figures is a classic problem of pattern recognition which can be solved in different ways. While there are several simple approaches such as distance or Bayes classification there are also some more complex ones such as support vector machines (SVM).

In 2010 Zhang et al. proposed a portable system which allows for automatic readout of counter values. The pattern recognition applies e.g. including morphology, grayscale conversion, edge detection and the Hough transformation (Zhang et al., 2010). Although the system is able to read out the counter values a person has to carry out the measurement by placing the system on the counter because the system is very expensive.

Another system for automatic readout was proposed by Shu et al. in 2007 (Shu et al., 2007). It uses a digital image processing system for character recognition.

The disadvantages of all methods discussed before are that they are expensive, that they require modification of the counter mechanics and that some of them also require persons to carry out the readout manually.

The system proposed in this paper is much cheaper because it consists of simple optoelectronic parts and therefore allows for real automated processing without requiring a person to start the readout.

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Furthermore it reads the actual counter value rather than parallel counting with an electronic counter.

3 SYSTEM ANALYSIS

A test setup was built for a type of counters in order to show that the proposed method is applicable. Each figure wheel is illuminated by two LEDs. The reflected light is measured by three photo transistors. This setup results in a vector of measured values consisting of nine dimensions.

Measurements showed how different external influences negatively affect the accuracy of the classification. Additionally to mechanical tolerances of the counters temperature fluctuation or scattered light have a negative effect on the classification. As shown in (Benyoucef et al., 2012) temperature drifts and scattered light intensity can be held as low as to allow for a correct classification of the figures on the figure wheels.

The influence of mechanical tolerances during production of the counters and printing of the figures are much more critical because they result in characteristic patterns for each figure, figure wheel, and counter. Those patterns have to be trained to a classification algorithm which is a laborious task to do.

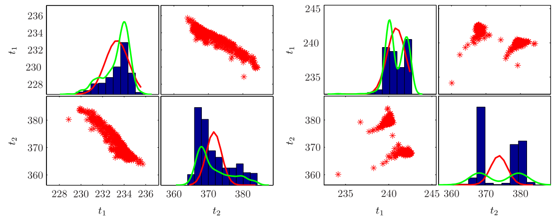
One important task is therefore to generalize the measured values in order to require only one set of training data for each type of counter.

For this generalization the classification results of a distance classifier, a Bayes classifier assuming a single or a double normal distribution, and an SVM in a strongly vibrating environment, resulting in maximum mechanical play, are analyzed in section 5.

4 CLASSIFICATION METHODS

We now assume that a set of data containing known pairs of figure wheel value and measured value is available. This data is used to analyze different classification methods with respect to complexity and computational efforts. For the latter efforts for training and classification have to be analyzed separately. The a priori information contained in our data set allows for performance analysis of the algorithms.

Distance Classifier. The simplest approach is based on a distance classifier. In Figures 1 (a) and (b)two of the nine available dimensions of a measurement of one figure are shown together with their respective histograms. The plot in red shows a single normal distribution fitted to the data. The plot in green shows the distribution function computed by the kernel density estimation method (KDE).



(a) Normal environment. (b) Vibrating environment.

Figure 1: Distribution of the figure 0 in two dimensions.

Based on the fact, that the measured values show either a single or double normal distribution (as shown in Figures 1 (a) and (b)), and the assumption, that the use of a double normal distribution leads to only small errors when instead the data form a single normal distribution, we always use the double normal distribution.

The estimations of the distribution parameters is done using the expectation maximization algorithm (EM algorithm) (Dempster et al., 1977).

After analyzing all clusters a newly measured value can be assigned to a figure by finding the minimum distance from the measured value to the subcluster of the distributions of each figure.

Bayes Classifier with Single Normal Distributions. Because of the disturbing influences described in section 3 the variances of the individual clusters and dimensions may differ. A distance classifier as described before does not respect this fact which leads to errors in heavily disturbed environments. In order to improve the performance in this case we now analyze a Bayes classifier assuming a single normal distribution.

In contrast to the distance classification the Bayes classifier includes the statistical characteristics of the feature vector for the classification of the figures. Starting point for the analysis is the feature vector $\boldsymbol{x}_m$ which has to be classified. The Bayes classifier decides in favor of the figure that maximizes its a posteriori probability

Bayes Classifier with Double Normal Distributions. In addition to the single normal distribution we take a double normal distribution into account for our analyzes. This is to improve classification results of distributions like the one shown in Fig. 1 (b).

Support Vector Machines. Support vector machines are used for classification as well as for regression tasks. They are a mathematical method for pattern recognition developed by Cortes and Vapnic in 1995 (Cortes and Vapnik, 1995). The goal is to place a separation plane between two clusters such that they are separated by the largest distance possible.

In order to solve nonlinear classification problems with this linear separation plane the data can be transformed into a higher-dimensional space (theoretically up to infinite dimensions) using a kernel function.

The advantage of SVM compared to Bayes classifier is that they do not need to assume a distribution function. The separation plane is placed such that the distance of the measured values of each cluster closest to the plane is maximal.

SVMs are only suitable for two-cluster situations. The decision between 10 clusters, as it is the case for counters, requires higher computation efforts. The extension to from two to 10 clusters was done using the one against one (OAO) and the one against all (OAA) methods. In the OAA case a radial basis function (RBF) was used as a kernel function. In the OAO case a linear, a polynomial and a radial basis function yielded equal results. Therefore the simple linear kernel function was used.

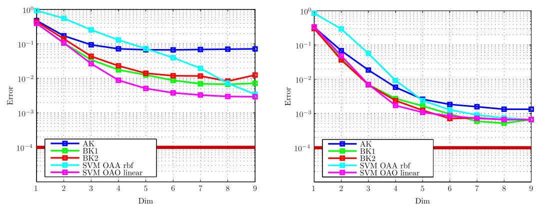
5 EXPERIMENTAL RESULTS

In this section the results of the different classification algorithms are shown. Figures 2 (a) and (b) show the resulting errors. The horizontal axis is scaled in numbers of used dimensions. Since there are many different ways of leaving some dimensions unanalyzed the mean of all possibilities is plotted. The vertical axis represents the classification error. The distance classifier is shown by the blue curve, the Bayes classifier with a single normal distribution in green, the Bayes classifier with a double distribution in red, the SVM with OAA in turquoise, and the SVM with OAO in violet. The red bar marks the error level of 10^{-4} which can be achieved by the given number of training data.

First 25 training values were used for each figure. The resulting number of errors is shown in Figure 2 (a). When the number of training values is increased the number of errors decreases for all classifiers (Figure 2 (b)).

It can be seen that the SVM with the OAA method produces more errors when using only few dimensions than the other classifiers. The reason for this is that the areas that cannot be classified nonambiguously by the OAA method become relatively large. If a measured value lies in this area it is marked as an error. This is a disadvantage compared to the Bayes classifier which does not apply a sharp separation line.

The best results are achieved by the SVM with the OAO method. This is more distinct when dealing with few training values because the few values do not contain enough statistical a priori information.



(a) 25 training values. (b) 250 training values.

Figure 2: Resulting errors.

6 GENERALIZATION

6.1 Iterative Method using Gray Values

Until now the problem to solve was to assign gray values to a number considering only one measurement. This leads to errors when training and test values result from different measurements. To demonstrate this the number detection system is modeled as a Hidden Markov Model (HMM). The iterative method requires the movement (increment or decrement) of the figure wheel to be recognized. This movement can be detected by computing the euclidean distance of two measurements and applying a threshold detection afterwards. This movement detection is not part of this paper; it is considered working correctly.

Usually the sequence of figures is known and identical among different types of counters. This knowledge can be used for the classification of measured gray values. Although the sequence of figures is determined this model does not describe the value change events as these depend on the actual system the counter is used in. After a first measurement the probability that the measured gray values describes a figure can be computed. Once a movement of the figure wheel is detected, this process is repeated yielding in a series of probabilities. In contrast to the methods described before the iterative method then classifies the counter value according to the maximum of the product of this probability sequence.

6.2 Iterative Method using Differences of Gray Values

Another way to improve the classification accuracy is to use differences of reflectivity values. This way offsets due to severals reasons including ambient temperature can be eliminated. This is especially advan-

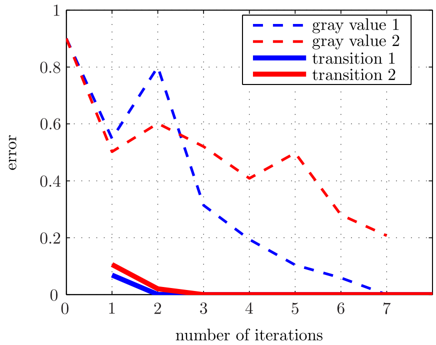


Figure 3: Resulting errors vs. sequence length for two counter wheels.

tageous for the generalization of the training values for different types of counters. The difference is directly computed in the 9-dimensional feature space.

In order to classify a figure sequence the reflectivity values of at least two consecutive figures are required. A longer sequence will lead to a higher probability of correct classification of this sequence.

In Figure 3 the resulting errors are plotted against the sequence length for two different figure wheels. The dashed lines represent the errors of the direct gray value classification. The errors of the classification of transitions are shown by the continuous lines. For this example 5000 reflectivity values measured at an ambient temperature of 20°C were analyzed. The 4000 training values were measured at 0°C on a different counter. It can easily be seen that the error rate decreases with increasing sequence length. Also the difference between the direct gray value classification and the classification of reflectivity value differences is directly visible. This effect is especially distinctive due to the combination of test and training values described above. The temperature difference between training and test measurement leads to an offset which is eliminated by computing the differences of gray values.

In conclusion the direct gray value classification yields good results when good-natured training and test values are used (cf. the sections above). If though training and test measurements are subject to different ambient conditions the analysis of differences of reflectivity values is advantageous.

7 CONCLUSIONS

In this paper a system for reading out a mechanical counter automatically was presented. It is based on the fact that different counter values have different light reflectivity coefficients. The main advantage is that the counter does not have to be modified and that the simple electronics are very cheap. This method can also be applied during the manufacturing of the counters in order to do a quality control test. The influence of external parameters can be reduced to such levels that a very precise classification of the figures can be achieved.

The different classification methods can be chosen according to desired application and available computation resources. The iterative method opens another application area. It allows for the analysis of different counters using one set of training data. An increasing number of counter value changes increases the chances of its correct recognition. If, instead of direct gray values, differences of reflectivity values are used offsets due to temperature and other influences can be eliminated. Since this method is especially useful for recognition of different counters of the same type this may be interesting for counter manufactures for post-production testing.

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