ICOUNTER
Development of an Optical Readout Method for Mechanical Counters

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Keywords: Mechanical counter, Bayes classifier, Nearest neighbors classifier, Pattern recognition, Gray scale recognition, Cluster analysis.

Abstract: Mechanical counters are still very common in electricity, water and gas meters. Automatic readout of the dial count without modifying the mechanics of the counter is only possible using expensive image processing methods. Therefore the topic of this report is a new method for automatically reading out the counter values without the need of additional mechanical or parallel electronic parts inside the counter. Instead the different reflection properties of the different digits are measured and evaluated. This is done using only simple electronic parts and a microcontroller.
In the first part of the paper the hardware for measuring the reflection values is presented. A model of this hardware with special emphasis on the influences of the environment is discussed in the next part. Following this, two classification methods, for distinguishing the digits are analyzed. For showing the properties of the new readout system measurements and simulations are given in the end.

1 INTRODUCTION

Mechanical counters are used in many different devices, such as for example electricity, water, and gas counters, cash mashines, and gambling machines. Most often mechanical counters are used because of their protection against manipulation. The readout of the counter values is typically done by a person writing down the values on paper or computers which involves high costs and makes continuous readout impossible. Therefore a possibility for automatically evaluating the counter value is sought. Most of the currently known methods for electronic readout use a parallel electronic counter which is connected to the mechanics of the counting unit. This does not read the actual counter value but it reads the value of the electronic counter. This undoes the advantage of protection against manipulation of the mechanical counters.

2 STATE OF ART

The evaluation of optically acquired counter values is done applying digital signal processing. Pattern recognition methods are used for the classification of the digits. Especially the area of image processing is concerned with finding a pattern in an optically recorded image of this pattern. One way of achieving this is based on the gray level recognition. Otsu has evaluated histograms of gathered images for this purpose (Otsu, 1979). A second application was described by (Martinez-Carballido et al., 2011). Another work concerned with the recognition of digits was carried out in the year 2006 (Qian et al., 2006). Many different methods can be applied in the area of the optical recognition of counter values (Shu et al., 2007). In 2010 Zhang et al. developed a portable optical system (Zhang et al., 2010). For the pattern recognition they applied different algorithms comprising including morphology, gray scale conversion, edge detection and the Hough transformation. The disadvantage of this method is that the readout of the counter values has to be done manually. Another approach is based on the optical scanning using a video camera. In 2007 Shu et al. presented a method for recording the values of electronic counters (Shu et al., 2007).

The disadvantages of the methods shown before are the fact that the data acquisition has to be done manually and that the presented readout units need expensive hardware. This is the basis for a new system. The main advantage of this system is that no modifi-

Benyoucef D., Held P. and Bier T. (2012).
ICOUNTER - Development of an Optical Readout Method fot Mechanical Counters.
In *Proceedings of the 1st International Conference on Pattern Recognition Applications and Methods*, pages 576-580
DOI: 10.5220/0003779605760580
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cation of the mechanics of the counter is needed and that the counter is read out directly without applying an additional parallel counter. Furthermore the electronic hardware presented in the following is small and inexpensive allowing for remote readout of the counter values.

3 REFLECTION FACTOR MEASUREMENT METHOD

The measurement of the reflection factors / gray value is following the block diagram shown in Figure 1. Each figure wheel is illuminated by two LEDs. The reflected light is measured by three photo transistors each. This assembly is attached to each figure wheel. In this report a counter with six figure wheels is used. The two light sources and the three light sinks result

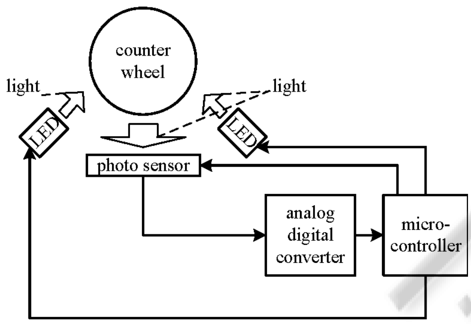


Figure 1: Structure of the measurement system.

in three illumination settings and 9 measurements for each figure wheel. After a measurement is completed the first figure wheel representing the lowest order digit is increased by one step. This way each measured value can be assigned to a counter value.

4 SYSTEM MODELING

In order to reduce the influence of external light a reference measurement is performed before each measurement. Afterwards the first LED is switched on and the reflected light is measured by the three optical sensors. The same procedure is performed for the second LED and for the simultaneous operation of the first and the second LED. The illumination with differently located LEDs results in a nine-dimensional feature vector $\vec{r}_m$, $m \in [0,\ldots,9]$ denoting the digit, which allows for the recognition of the digits. The formation of this vector is shown in equation (1). The operation of LED_1 yields the reflection values t_1 through t_3. Illumination by LED_2 is represented by t_4 through t_6. The last three elements are the result of the simultaneous operation of the two LEDs.

$$\vec{r}_m = \left[\underbrace{t_1 \quad t_2 \quad t_3}_{LED_1} \quad \underbrace{t_4 \quad t_5 \quad t_6}_{LED_2} \quad \underbrace{t_7 \quad t_8 \quad t_9}_{LED_{1+2}} \right]^T \tag{1}$$

For the following investigations the first three figure wheels are used. After 64 measurements of each wheel the counter value is increased by one. This has to be repeated 1000 times in order to measure each possible digit combination of the first three wheels.

5 SYSTEM ANALYSIS

The measurement results are influenced by various disturbances. The main factors are the variations of the ambient temperature and the scattered light. For a reliable recognition of each digit from the feature vector $\vec{r}_m$ it is required to minimize these influences.

5.1 Influence of Scattered Light

The influence of scattered light can be divided into constant and random light sources. The constant light sources are modeled as an offset l_i which results from extraneous light and superposes the actually measured value t_i, $i \in [1,...,9]$.

$$t_i' = t_i + l_i \tag{2}$$

Light sources that vary during the measurement are eliminated by a reference measurement at the beginning of the process. However the operating point of the photo transistors may be shifted by strong extraneous light sources. This influences is diminished by the use of the aperture. Non-constant (sporadic) light sources are modeled as a random variable s_i. In the case of an incandescent lamp which is turned on and off periodically a normal distribution with non-zero mean is assumed because of the integral behavior of the lamp. The random variable is added to the actually measured value as well.

$$t_i' = t_i + s_i \tag{3}$$

When considering the expected value of t_i' the random variable s_i becomes a constant offset.

$$\mathcal{E}\{t_i'\} = \mathcal{E}\{t_i\} + \mathcal{E}\{s_i\} = t_i + \mu_{s_i} \tag{4}$$

Equation (4) shows that the influence of random extraneous light can be eliminated by simple averaging. As for the constant light source the resulting offset can be compensated by a reference measurement.

5.2 Tolerance of the Counter

Due to mechanical tolerances each figure wheel has a mechanical slackness. This increases the dispersion of the measurement results. Additionally a figure wheel does not always rest in a defined position which changes the reflection factors t_i. For the analysis of this problem several measurements were performed where a figure wheel reaches each digit multiple times. This results in a vector of reflection factors

$$\vec{t}_{i_k} = \begin{bmatrix} t_{i_1} & t_{i_2} & \dots & t_{i_n} \end{bmatrix}^T \tag{5}$$

with t_{i_k} denoting the k-th realization of the i-th reflection factor. The reflection factor can be modeled as the sum of the noise free reflection factor and the influence of the mechanical play

$$t_{i_k} = t_i + m_i. \tag{6}$$

The mechanical play is modeled as a random variable where the properties of this variable have to be defined exactly. For this purpose the measurements of t_i are evaluated. First the probability density function of m_i is used. The probability densities of the detector signals t_3 and t_9 are shown in Figure 2. It is easy to see

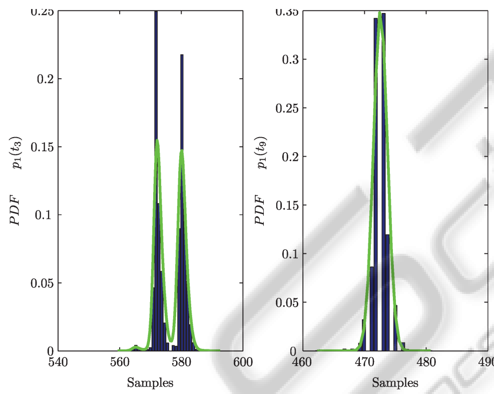


Figure 2: Probability density function, Position 2, Digit 1, LED 1 and 2.

that the signal t_3 forms a double normal distribution whereas the signal t_9 shows a signal normal distribution. The evaluation of all sensor signals for all digits shows that there is always either a single or a double peak distribution which is the result of the mechanical slackness of the figure wheels. The two-dimensional distribution of the sensor signals is shown in Figures 3 and 4 as an example for this.

6 CLUSTER ANALYSIS

Based on the system analysis in the previous section two approaches for the recognition of digits on the

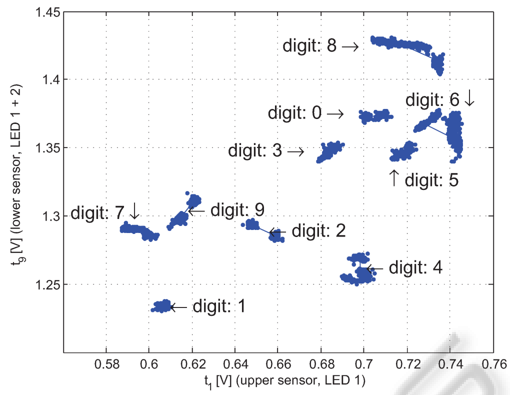


Figure 3: Distribution of the clusters of the first figure wheel with the features t_1 and t_9.

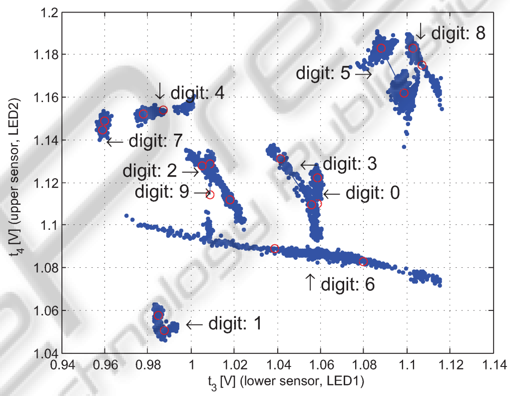


Figure 4: Distribution of the clusters of the second figure wheel with the features t_3 and t_4.

figure wheel are shown in this section. The basis for both algorithms is the separability of the digits in the feature space. As seen in Figures 3 and 4 it is possible to separate the values of each digits in the two-dimensional space. The first approach is based on the k-Nearest Neighbors algorithm (kNN) with the modification that only single reference points are used. The second approach uses a Bayes classifier.

6.1 Modified k-Nearest Neighbor Algorithm

In order to reduce the computation complexity and memory requirements the k-Nearest Neighbor algorithm was modified. The new algorithm uses two reference points for each digit. These reference points have to be determined in advance. The two reference points are needed, because some distributions of the reflection factors t_i have, as shown in Figure 2, two local maxima.

The reference are determined by computing the expected value $\mathcal{E}\{\vec{r}_m\} = \vec{\mu}_{r_m}$ of the whole cluster of one digit m and the reflection value t_1 which has the longest distance d_1 to the expected value $\vec{\mu}_{r_m}$. All reflection values with distance to the reflection value t_1 smaller than the distance to the expected value d_1 are assigned to the partial cluster $c = 1$. After this the reflection value t_2 with the longest distance d_2 to the expectation value $\vec{\mu}_{r_m}$ is computed. This value must be in the whole cluster but it must not be in the partial cluster $c = 1$. All reflection values with distance to t_2 smaller than d_2 are assigned to the partial cluster $c = 2$. This is done for all nine dimensions. After the assignment of the values to the partial cluster the expected value is computed for each of those partial clusters $c = 1$ and $c = 2$.

$$\vec{rz}_m^c = \mathcal{E}\{\vec{r}_m^c\} \qquad c \in \{1,2\} \tag{7}$$

A disadvantage of this method is that the statistics of the distribution of the measured values is not included in the recognition process. This may lead to wrong results when dealing with large variances of the probability density functions.

6.2 Bayes Classifier

In contrast to the classification based on the euclidean distance the Bayes classifier makes use of the statistical characteristics of the values to be separated. Starting point is the feature vector $\vec{r}_m$ which should be used for deciding which number it represents. The Bayes classifier assigns the value to the cluster which maximizes the a-posteriori probability $P(m|\vec{r}_m)$.

$$e = \arg \max_{m=1,\ldots,9} P(m|\vec{r}_m) \tag{8}$$

Using the Bayes theorem (Hoffmann, 1997) the decision rule can be expressed in values that can be determined from training values.

$$e = \arg \max_{m=1,\ldots,9} \{P(\vec{r}_m|m) \cdot P(m)\} \tag{9}$$

$P(m)$ is the a-priori class probability and $P(\vec{r}_m|m)$ is the conditional probability that the feature vector $\vec{r}_m$ belongs to the class m.

As shown in section 5.2 the probability density functions of the feature vectors $\vec{r}_m$ follow a single or double normal distribution. Equation (10) declares the multi-dimensional probability density function of a single normal distribution (Hoffmann, 1997).

$$p(\vec{r}_m|m) = \frac{1}{(2\pi)^{N/2} \cdot |\mathbf{K}_m|^{1/2}} \cdot \exp\left(-\frac{1}{2} \cdot (\vec{r}_m - \vec{\mu}_{r_m})^T \cdot \mathbf{K}_m^{-1} \cdot (\vec{r}_m - \vec{\mu}_{r_m})\right) \tag{10}$$

$\vec{\mu}_{r_m}$ is the expected value of the feature vector $\vec{r}$ of the class m and $\mathbf{K}_m$ is the covariance matrix of the class m.

7 EXPERIMENTAL RESULTS

The analysis of the classification algorithms is based on the measurements of mechanical counters. The data were separated into the training sequence for the estimation of the parameters for the algorithms and a test set for judging the quality of the algorithms. The quality criterion was the classification error.

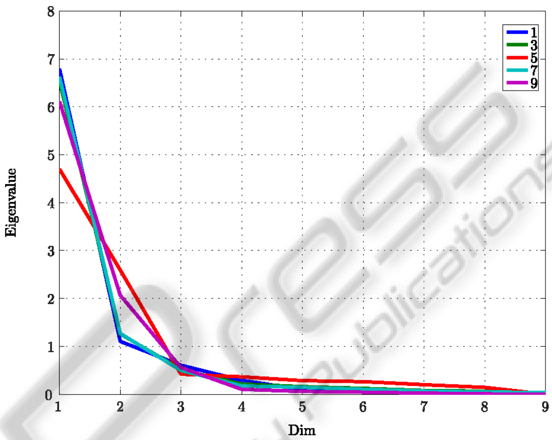
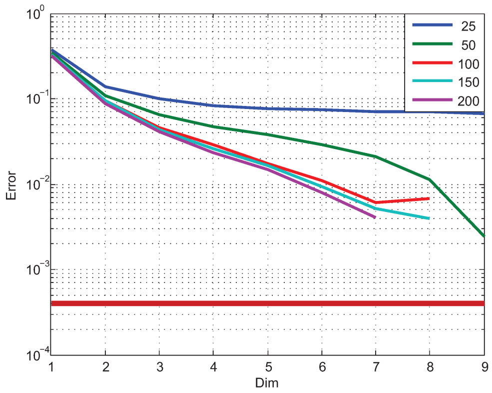


Figure 5: Analysis of the eigenvalues of the covariance matrix $\mathbf{K}_m$ of the digits 1, 3, 5, 7, and 9.

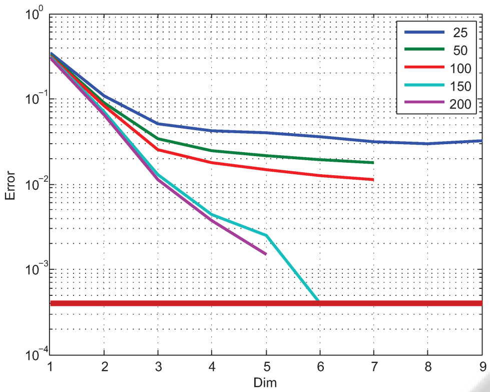
The eigenvalues of the covariance matrix for each of the nine digits is shown in Figure 5. The figure shows a distinct difference in the magnitude of the eigenvalues. The condition number

$$\chi(\mathbf{K}_m) = \frac{\lambda_{max}}{\lambda_{min}}, \tag{11}$$

the ratio of the largest and the smallest eigenvalue, is around 1000 for all digits. This means that there is a strong correlation between the individual features. This represents the physical dimensions of the measurement board because the optical sensors are placed very close together. So all three sensors of one figure wheel measure approximately the same reflection factor. A comparison of the two classification algorithms is shown in Figures 6 (a) and (b). In both graphs the classification error is plotted against the dimension of the feature vector $\dim\{\vec{r}_m\}$. All combinations of the features t_i in dependence on the dimension were evaluated. The classification error was obtained by computing the mean value. Therefore the curves show an approximation of the maximum error. The data used for the analysis were the test set values described in the beginning of this section. The red line at an error of $\frac{1}{2500}$ marks the minimum error level that can be reached. This is restricted by the available number of values. The comparison of the algorithms shows that the modified Nearest Neighbor algorithm



(a) Modified Nearest Neighbor algorithm.



(b) Bayes classifier.

Figure 6: Investigation of the classification error for different numbers of training values for the parameter estimation. The simulation is based on 2500 values of the test set.

produces considerably more errors 6 (a). When using 200 training values and requiring an error of 1 % the Bayes classifier needs three dimensions whereas the modified Nearest Neighbor classifier needs six dimensions. The error rate goes down to the minimum if 8 dimensions are given. In the system all 9 dimensions are used so the modified Nearest Neighbors algorithm is advantageous because of its low computation complexity. The simulations show that the Bayes classifier reaches zero error (which cannot be shown in the logarithmic plot) at 8 dimensions and 50 training values as well.

8 CONCLUSIONS

In this report a system allowing the automatic readout of the digits of mechanical counters was presented. This method makes use of reflection values of the figure wheels. The special advantage of the system is that it does not require modifications of mechanics of the counters and that the electronic parts used are inexpensive. This method is not only restricted to this special application but it can be used where ever a limited number of symbols have to be recognized. Another application may be for the manufacturers the continuous check of the counter operation during the production process and the quality assurance.

In this report the different influences of the environment, such as extraneous light and the mechanical tolerances of the counter, were analyzed. It was shown that the influence of these disturbances can be reduced to a level, that allows the error free recognition of the digits, by different means.

REFERENCES

Hoffmann, R. (1997). *Signalanalyse und -erkennung: Eine Einführung für Informationstechniker.* Springer, 1 edition.

Martinez-Carballido, J., Alfonso-Lopez, R., and Ramirez-Cortes, J. (2011). License plate digit recognition using 7x5 binary templates at an outdoor parking lot entrance. In *Electrical Communications and Computers (CONIELECOMP), 2011 21st International Conference*. IEEE.

Otsu, N. (1979). A threshold selection method from gray-level histograms. In *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, VOL. SMC-9, NO. 1*. IEEE.

Qian, J., Qian, D., and Zhang, M. (2006). A digit recognition system for paper currency identification based on virtual instruments. In *ICIA 06*. IEEE.

Shu, D., Ma, S., and Jing, C. (2007). Study of the automatic reading of watt meter based in image processing technology. In *Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference*. IEEE.

Zhang, Z., Chen, G., Li, J., Ma, Y., and Ju, N. (2010). The research on digit recognition algorithm for automatic meter reading system. In *Intelligent Control and Automation (WCICA), 2010 8th World Congress*. IEEE.