Recognitions of Tonal Sound and License Plate Character Using Filter-driven Template Matching

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Abstract— **In this paper, we propose a filter-driven template matching scheme which is capable of recognizing one-dimensional signals and two-dimensional patterns. Our method is the improvement of the conventional template matching, meanwhile, it can be considered as a restoration process. We estimate a filter and then apply it to reference signal/pattern, which makes the filtered reference signal/pattern as similar as possible to the query one. In the literature, two common used approaches were available for filter estimation, namely least squares estimator (LSE) and quadratic programming (QP). Afterward, computing the errors between the filtered signals/patterns and the query one, one of filtered signals/patterns with minimum error is the best resultant of recognition. The proposed method is robust against several operations, including scaling/amplifying, filtering, translation and noise addition. Experiment results demonstrate that the filter-driven template matching scheme is superior to the conventional template matching in recognition of one-dimensional tonal sounds and two-dimensional license plate characters.**

I. Introduction

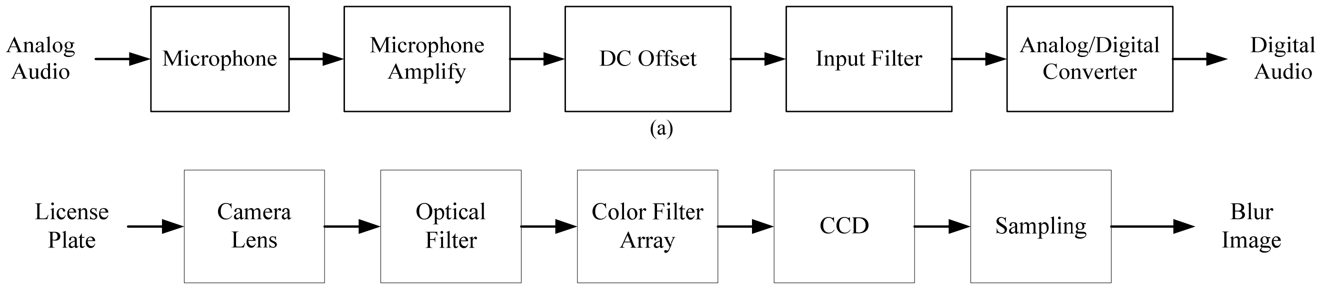
Template matching is a well-known technique for finding a reference signal that matches to the query one. Two measurements are frequently used to represent the degree of similarity between query signal and reference signal: sum of square differences (SSD) and correlation. Another measurement, the discriminative signal-to-noise ratio (DSNR) was used as a matching criterion to recognize templates [1, 2]. Usually, template matching is a way to implement pattern recognition, object detection and tracking, video compression (motion vector estimation), etc. However, an original signal could be altered by various operations, such as filtering, offsetting, scaling, re-sampling, translation, and noise addition. Those operations degrade the quality of original signal so that it is difficult to recognize signal accurately. Fig.1 depicts those operations exist in digital audio and image capturing processes.

In the past, researchers investigated how to detect object based on matched spatial filter (MSF) [3]. An MSF takes template as a filter by measuring correlation as a criterion for checking similarity. However, an MSF cannot perform invariant recognition. In order to solve this problem, a synthetic discriminant function filter [4], the combination of matched spatial filters, was presented to handle geometric distortion and multiclass pattern recognition. Rao and Ben-Arie [1, 2] presented a multiple-template-matching scheme. They constructed a set of template-similar basis functions based on signal expansion, and it had good performance against noise, superposition and severe occlusion. Kim and Araújo [5] proposed a grayscale template matching algorithm which is invariant to rotation, scale, translation, brightness and contrast of image. Their method was composed of three cascade filters, including circular sampling filter, radial sampling filter, and template matching filter, and it is much faster than brute force algorithm in template matching. Recently, Anderson et al. [6, 7] introduced a method to fast implement template matching. Dual-bound of Euclidean distance measurement in Anderson et al.'s method is helpful to reduce computing time.

In this work, we design a way to recognize signal using filter-driven template matching (FTM). One hypothesis is that a query signal is modeled as the resultant of a reference signal operated with a filter. The FTM method can utilize least square estimator (LSE) or quadratic programming (QP) to estimate filter which makes error between a query signal and a filtered signal small. As multiple templates are available, the multiple corresponding filters are estimated. The query signal will be treated as one of reference signals according to the minimum error. The proposed scheme is robust against several operations, such as scaling/amplifying, filtering, translation and noise addition. Performance evaluation by measuring a rank value is presented in this work, and the rank value is further used to construct an accumulation histogram as a major criterion of evaluation. The rest of this paper is organized as follows: the proposed method how to implement recognition of signals and images is elaborated in Section II. A way to evaluate recognition performance is introduced in Section III. Experiment results will be shown in Section IV, and the concluding remarks will be drawn in Section V.

II. Filter-driven Template Matching

Fig.1 depicts that various operations degrade quality of signal. For example, filtering operation exists in both audio and image capturing processes. Unfortunately, the filtering operations are unrevealed to public because they are business secrets. This work we intend to use a linear filter and a sampling operation to model relationship between a query



(b)

Fig.1. Block diagrams of (a) digital audio capturing process, and (b) digital image capturing process.

signal and a reference signal, which is expressed as $y \approx \mathrm{S}(x \otimes F)$, where x, y and F represent the reference signal, the query signal and the filter, respectively. The function $\mathrm{S}(\cdot)$ denotes a sampling operation, and the symbol '$\otimes$' is a convolution operation. In what follows, we shall introduce how to estimate filter and implement recognition using filter-driven template matching (FTM), simultaneously.

A. Recognition of Tonal Sound

The proposed recognition process of one-dimensional tonal sound consists of three steps: offset subtraction, filter estimation, and tonal sound recognition. Sum of square differences (SSD) is a measurement to judge degree of similarity between query signal and reference signal. However, SSD is very sensitive to signal offsetting, but correlation is not. However, the proposed scheme needs to measure the SSD value as a criterion of recognizing templates. To prevent offset degrading recognition performance, the offset subtraction is operated to both query signal and reference signal in advance. The query signal (S_{Q}) and the reference signal (S_{R}) are subtracted by their offsets, which are expressed as $\hat{S}_{\mathrm{Q}}=S_{\mathrm{Q}}-\mu_{\mathrm{Q}}$ and $\hat{S}_{\mathrm{R}}=S_{\mathrm{R}}-\mu_{\mathrm{R}}$, where $\hat{S}_{\mathrm{Q}}$ and $\hat{S}_{\mathrm{R}}$, respectively, denote the offset-free query signal and the offset-free reference signal. μ_{Q} and μ_{R} represent the averages of S_{Q} and S_{R}, respectively.

We assume that $\hat{S}_{\mathrm{Q}}$ is similar to the filtered signal $\hat{S}_{\mathrm{F}}$ which is the resultant of $\hat{S}_{\mathrm{R}}$ operated with a filter F, where $F=[f_0, f_1, \ldots, f_{2L}]$. The lengths of F, S_{R}, S_{Q} and $\hat{S}_{\mathrm{F}}$ are set as $2L+1$, L_{R}, L_{Q} and L_{Q}, respectively. In addition, L_{R} is either equal to or larger than L_{Q}, that is $L_{\mathrm{R}} \geq L_{\mathrm{Q}}$. The coefficient of $\hat{S}_{\mathrm{F}}$ is computed and expressed as follows,

$$\begin{aligned} &\hat{S}_{\mathrm{F}}(j) = \sum_{j=-L}^{+L} \hat{S}_{\mathrm{R}}\big(u(j)+k\big) \cdot f_{L+k}, \\ &\text{where } u(j) = round\left(\tfrac{j}{L_{\mathrm{Q}}-1} \times (L_{\mathrm{R}}-1)\right), \\ &\qquad j \in \{0,1,\ldots,L_{\mathrm{Q}}-1\}, \\ &\qquad u(j) \in \{0,1,\ldots,L_{\mathrm{R}}-1\}. \end{aligned} \tag{1}$$

The i-th sum of square differences (which is abbreviated as ssd_i) between the offset-free query signal $\hat{S}_{\mathrm{Q}}$ and the i-th filtered signal $\hat{S}_{\mathrm{F},i}$ is measured according to,

$$ssd_i = \sum_{j=0}^{L_{\mathrm{Q}}-1} \left|\varepsilon_i(j)\right|^2 = \sum_{j=0}^{L_{\mathrm{Q}}-1} \left|\hat{S}_{\mathrm{Q}}(j) - \hat{S}_{\mathrm{F},i}(j)\right|^2, \tag{2}$$

where $\varepsilon_i(j)$ is the difference between the j-th coefficients of $\hat{S}_{\mathrm{Q}}$ and $\hat{S}_{\mathrm{F},i}$. Equation (1) is modified and rewritten to a matrix form as expressed in (3). It is obvious that $\hat{S}_{\mathrm{F}}$ is replaced by $\hat{S}_{\mathrm{Q}}$ for estimating filter. Subsequently, the filter coefficients are estimated using LSE, and then the estimated filter is put into (1) to obtain the filtered signal.

Moreover, QP is available to estimate filter in this work. According to (1) and (2), the form of quadratic programming is expressed as follows,

$$\begin{aligned} \text{Minimize}: \quad & \sum_j \varepsilon_j^2, \\ \text{Subject to}: \quad & \varepsilon_j = \hat{S}_{\mathrm{Q}}(j) - \hat{S}_{\mathrm{F},i}(j), \\ & \hat{S}_{\mathrm{F}}(j) = \sum_{j=-L}^{+L} \hat{S}_{\mathrm{R}}\big(u(j)+k\big) \cdot f_{L+k}, \\ & -\infty \leq f_j \leq \infty. \end{aligned} \tag{4}$$

Putting the estimated filter into (1), the filtered signal is obtained as well. In fact, using both the LSE and QP methods can obtain the same estimated filter as well as the filtered signal. During signal recognition, there are N reference tonal sounds compared with a query tonal sound, then, the N filters and the corresponding filtered tonal sounds are obtained. Consequently, the query tonal sound is identified as the i-th reference one with the minimum SSD value according to,

$$i^* = \operatorname*{arg\,min}_{i \in \{0,1,\ldots,N-1\}} ssd_i \cdot \tag{5}$$

B. Recognition of License Plate Characters

We also employ the filter-driven template matching scheme to implement recognition of license plate character,

$$\begin{bmatrix} \hat{S}_{\mathrm{Q}}(0) \\ \hat{S}_{\mathrm{Q}}(1) \\ \vdots \\ \hat{S}_{\mathrm{Q}}(L_{\mathrm{Q}}-1) \end{bmatrix} \approx \begin{bmatrix} \hat{S}_{\mathrm{R}}\big(u(0)-L\big) & \hat{S}_{\mathrm{R}}\big(u(0)-L+1\big) & \cdots & \hat{S}_{\mathrm{R}}\big(u(0)+L\big) \\ \hat{S}_{\mathrm{R}}\big(u(1)-L\big) & \hat{S}_{\mathrm{R}}\big(u(1)-L+1\big) & \cdots & \hat{S}_{\mathrm{R}}\big(u(1)+L\big) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{S}_{\mathrm{R}}\big(u(L_{\mathrm{Q}}-1)-L\big) & \hat{S}_{\mathrm{R}}\big(u(L_{\mathrm{Q}}-1)-L+1\big) & \cdots & \hat{S}_{\mathrm{R}}\big(u(L_{\mathrm{Q}}-1)+L\big) \end{bmatrix} \begin{bmatrix} f_0 \\ f_1 \\ \vdots \\ f_{2L} \end{bmatrix} \tag{3}$$

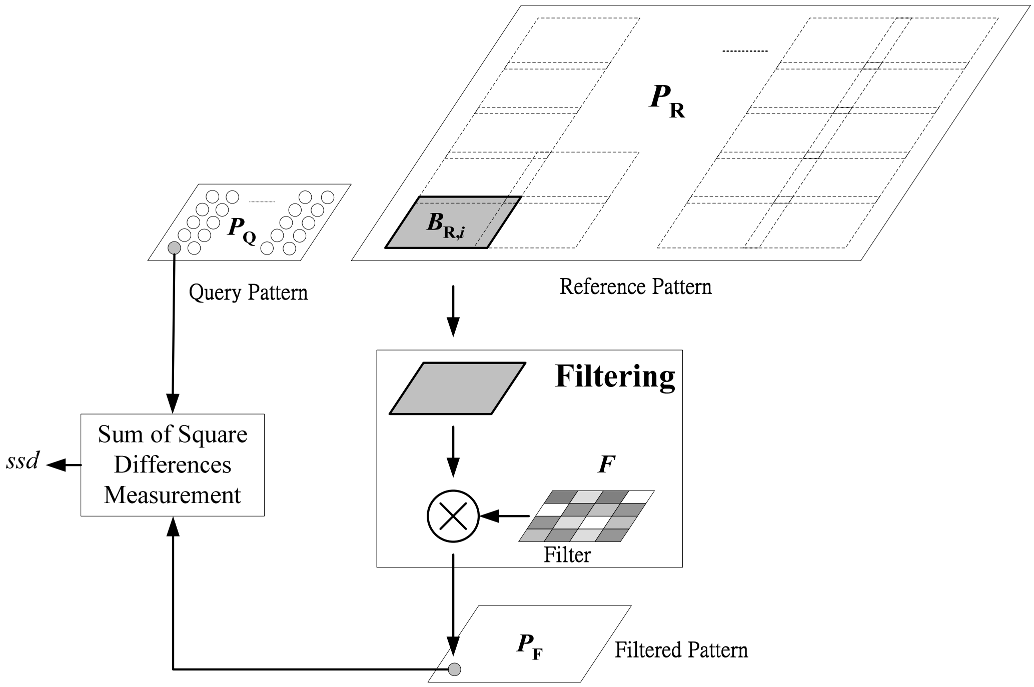


Fig.2. Relationship of query pattern P_{Q}, reference pattern P_{R}, and filtered pattern P_{F}

which is similar to recognition of tonal sound. Assume that P_{Q} and P_{R}, respectively, represent the query pattern and the reference pattern, and P_{F} is called the filtered pattern which is derived from P_{R} operated with a two-dimensional filter F. The dimensions of P_{R}, P_{Q}, and P_{F} are $W_{\mathrm{R}}\times H_{\mathrm{R}}$, $W_{\mathrm{Q}}\times H_{\mathrm{Q}}$, and $W_{\mathrm{Q}}\times H_{\mathrm{Q}}$, respectively. Fig.2 shows the relationship among P_{Q}, P_{R} and P_{F}. A two-dimensional filter F of size $W_{\mathrm{F}}\times H_{\mathrm{F}}$ is defined below,

$$F=\begin{bmatrix} f_{0,0} & f_{1,0} & \cdots & f_{W_{\mathrm{F}}-1,0} \\ f_{0,1} & f_{1,1} & & f_{W_{\mathrm{F}}-1,1} \\ \vdots & \vdots & \ddots & \vdots \\ f_{0,H_{\mathrm{F}}-1} & f_{1,H_{\mathrm{F}}-1} & \cdots & f_{W_{\mathrm{F}}-1,H_{\mathrm{F}}-1} \end{bmatrix}, \tag{6}$$

where W_{F} and H_{F}, respectively, represent the width and the height of the filter. The variable $f_{i,j}$ denotes the (i,j)-th coefficient in F, where $0 \le i \le W_{\mathrm{F}}-1$ and $0 \le j \le H_{\mathrm{F}}-1$.

In the first step, a reference pattern is divided into $W_{\mathrm{Q}}\times H_{\mathrm{Q}}$ blocks. The divided blocks (which are expressed as $B_{\mathrm{R},i}$ as shown in Fig.2) are overlapped in P_{R}, the ratio of the overlapped area between two neighboring blocks is 50%. The dimensions of B_{R} and F are defined as $W_{\mathrm{F}}=\lfloor 2W_{\mathrm{R}}/(W_{\mathrm{Q}}+1)\rfloor$ and $H_{\mathrm{F}}=\lfloor 2H_{\mathrm{R}}/(H_{\mathrm{Q}}+1)\rfloor$. The pixel value of a filtered pattern is derived by calculating the product of $B_{\mathrm{R},i}$ and F based on the following equation:

$$P_{\mathrm{F},i}=\sum_{u=0}^{W_{\mathrm{F}}-1}\sum_{v=0}^{H_{\mathrm{F}}-1} B_{\mathrm{R},i}(u,v)\cdot f_{u,v} \quad \text{and} \quad 0 \le P_{\mathrm{F},i} \le 255, \tag{7}$$

where $B_{\mathrm{R},i}(u,v)$ denotes the (u,v)-th pixel value of the i-th divided block, and $P_{\mathrm{F},i}$ is the i-th pixel value of the filtered pattern. The sum of square differences (ssd) between P_{Q} and P_{F} is given by,

$$ssd=\sum_{i=0}^{W_{\mathrm{Q}}\times H_{\mathrm{Q}}-1}\varepsilon_i^2=\sum_{i=0}^{W_{\mathrm{Q}}\times H_{\mathrm{Q}}-1}\left(P_{\mathrm{Q},i}-P_{\mathrm{F},i}\right)^2, \tag{8}$$

where $P_{\mathrm{Q},i}$ represents the i-th pixel value of query pattern.

Using the LSE and QP methods to estimate two-dimensional filter severs as the second step. In the LSE method, equation (7) is modified and rewritten to a matrix form which is similar to (3) as expressed in (9), where P_{F} is replaced by P_{Q}. The P_{Q} and $B_{\mathrm{R},i}$ are known, therefore, the filter coefficients can be determined accordingly. Putting the estimated filter into (7) yields the filtered pattern. The drawback of LSE is that we cannot exactly control the pixel value of filtered pattern ranging from 0 to 255. For this reason, QP is used instead of LSE, and the constraint of pixel value is set in QP. To rewrite (7) and (8) to the form of quadratic programming, it is expressed as follows,

$$\begin{bmatrix} P_{\mathrm{Q},0} \\ P_{\mathrm{Q},1} \\ \vdots \\ P_{\mathrm{Q},W_{\mathrm{Q}}\times H_{\mathrm{Q}}-1} \end{bmatrix} \approx \begin{bmatrix} B_{\mathrm{R},0}(0,0) & B_{\mathrm{R},0}(0,1) & \cdots & B_{\mathrm{R},0}(W_{\mathrm{F}}-1,H_{\mathrm{F}}-1) \\ B_{\mathrm{R},1}(0,0) & B_{\mathrm{R},1}(0,1) & \cdots & B_{\mathrm{R},1}(W_{\mathrm{F}}-1,H_{\mathrm{F}}-1) \\ \vdots & \vdots & \ddots & \vdots \\ B_{\mathrm{R},W_{\mathrm{Q}}\times H_{\mathrm{Q}}-1}(0,0) & B_{\mathrm{R},W_{\mathrm{Q}}\times H_{\mathrm{Q}}-1}(0,1) & \cdots & B_{\mathrm{R},W_{\mathrm{Q}}\times H_{\mathrm{Q}}-1}(W_{\mathrm{F}}-1,H_{\mathrm{F}}-1) \end{bmatrix} \begin{bmatrix} f_{0,0} \\ f_{0,1} \\ \vdots \\ f_{W_{\mathrm{F}}-1,H_{\mathrm{F}}-1} \end{bmatrix} \tag{9}$$

$$\begin{aligned} &\text{Minimize}: \quad \sum_i \varepsilon_i^2 \\ &\text{Subject to}: \quad \varepsilon_i = P_{\mathrm{Q},i} - P_{\mathrm{F},i} \\ &\qquad P_{\mathrm{F},i} = \sum_{u=0}^{W_\mathrm{F}-1}\sum_{v=0}^{H_\mathrm{F}-1} B_{\mathrm{R},i}(u,v)\cdot f_{u,v} \\ &\qquad 0 \le P_{\mathrm{F},i} \le 255, \\ &\qquad 0 \le f_{u,v} \le 1. \end{aligned} \tag{10}$$

Subsequently, the estimated filter is put into (7) to yield the filtered pattern as well. During character recognition using the FTM scheme, there are N reference patterns compared with a query pattern. The N estimated filters and the corresponding filtered patterns are obtained. Consequently, the query pattern is identified as one of the reference patterns with the minimum SSD value.

III. Performance Evaluation

In this section a measurement, rank value (r), is defined for evaluation of recognition performance. Calculating SSD values between a query signal and N reference signals, those SSD values are sorted from the smallest value to the largest one. When the k-th reference signal is the ground truth of the query signal, the rank value is the index of ssd_k among the N sorted SSD values. Ideally, the best resultant of recognition occurs at r=1, which means that the value of ssd_k is the smallest among N reference signals. On the other hand, the worst resultant of recognition occurs at r=N.

Subsequently, rank histogram and accumulation histogram are established based on the rank value, which are defined below,

$$Hist(i) = \frac{1}{M}\sum_{j=0}^{M-1}\delta[r_j - i], \tag{11}$$

$$AHist(i) = \sum_{j=1}^{i} Hist(j), \tag{12}$$

where $Hist(i)$ and $AHist(i)$ are, respectively, the i-th values of the rank histogram and the accumulation histogram, and $i\in\{1, 2, \ldots, N\}$. r_j denotes the rank value of the j-th query signal, and M is the total number of the query signals tested in experiments. $\delta(\cdot)$ is the Dirac delta function.

IV. Experiment Results

Three experiments were implemented in this paper. The first two experiments were recognition of one-dimensional signal/sound, and the rest of experiments were recognition of blurred license plate characters.

A. Recognition of One-dimensional Signals

In the first experiment three signals were tested and treated as the query signals shown in Fig.3(a), they were sine wave (R_s), square wave(R_q) and saw tooth wave (R_w). Every signal was of length 1001×1 expressed as follows,

$$\begin{aligned} &R_\mathrm{s}[i] = \sin\left(\tfrac{2\pi i}{1000}\right), \quad 0 \le i \le 1000, \\ &R_\mathrm{q}[i] = \begin{cases} 1, & 0 \le i < 500 \\ -1, & 500 < i \le 1000, \\ 0 & \text{otherwise} \end{cases} \\ &R_\mathrm{w}[i] = \begin{cases} \tfrac{i}{499}, & 0 \le i < 500 \\ \tfrac{i-1000}{499}, & 500 < i \le 1000. \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{13}$$

The three chosen signals were corrupted with scale, translation, offsetting, down-sampling and noise addition, which were shown in Fig.3(b), and the corruption formulation was expressed as follows,

$$\begin{aligned} &R'_k[i] = \begin{cases} 5R_k[i-100]+5, & 100 \le i \le 1000 \\ \zeta[i], & \text{otherwise} \end{cases} \\ &T_k[j] = R'_k[3j], \end{aligned} \tag{14}$$

where R'_k is the j-th synthesized signal, and $T_k[j]$ is the j-th coefficient of the k-th corrupted signal, $0 \le j \le 333$ and $k\in\{$s, q, w$\}$. The $\zeta[i]$ denotes the i-th noise value. For parameter setting, the half-length of filter was set L=150. The resultants of using LSE and QP methods were the same to each other. Table I lists the SSD values between the filtered signal (R'_k)

Table I. Sums of square differences between filtered signal (R'_k) and corrupted signal (T_k) by three methods

Method		R'_s	R'_q	R'_w	Rank
Direct Signal Sampling	T_s	10982.12	**10926.17**	11344.62	2
	T_q	15072.87	**14950.88**	15715.74	1
	T_w	11049.60	**10896.07**	11372.56	3
Signal Averaging	T_s	11049.60	**10896.07**	11372.56	2
	T_q	15164.09	**14888.46**	15686.84	1
	T_w	**9887.26**	9924.02	10010.44	3
Proposed Method	T_s	**130.32**	558.55	808.36	1
	T_q	1214.68	**85.13**	674.02	1
	T_w	1065.50	270.35	**89.56**	1

and the corrupted signal (T_k), where the bold font represents the minimum value. Fig.3(c) shows the best filtered signals corresponding to the corrupted signals. It is obvious that our method is superior to the other approaches in terms of performance of signal recognition.

B. Recognition of Tonal Sounds

For recognition of tonal sound, there were seven kinds of pitches in **C** major captured with 44.1kHz sampling rate, and the tonal sounds of these pitches were tested and treated as reference sounds, including Do, Re, Mi, Fa, Sol, La, and Si. The reference sounds were corrupted with 13 operations and then yielded 91 query sounds, these operations involved amplifying, translation, noise addition, down-sampling (22 kHz, 11 kHz and 8 kHz), lowpass filtering, highpass filtering, low shelf filtering, high shelf filtering, amplitude halving of fundamental frequency, and amplitude doubling of 1st and 2nd harmonics frequencies. We used a 301-length filter in the FTM scheme, and the estimated filter by using the LSE and QP were the same. Fig.4 illustrates the recognition results of tonal sounds via accumulation histogram. Apparently, the proposed scheme is superior to direct sampling and average filtering approaches, because the accumulation histogram of our method is much closer to that of the ideal case.

C. Recognition of License Plate Characters

Thirty-five reference patterns of license plate character were available in the experiment, and the dimension of every reference pattern was normalized to 60×120. We tested 1518 license plate characters and treated them as query patterns which included 10 kinds of digits and 25 kinds of alphabets, where the alphabet ‘O’ was excluded. The colorful character is transformed into gray-level patterns. The size of query pattern ranged from 65 pixels to 5000 pixels. Fig.5 shows the reference patterns and some characters. The FTM scheme utilized the LSE and QP methods to estimate filter, and then the filtered pattern was yielded accordingly.

In order to demonstrate the efficiency of filter estimation, we used an average filter instead of estimated filter and a direct sampling to yield filtered pattern. Fig.6 illustrates the accumulation histograms of the ideal case and four comparison methods. Apparently, the proposed method using quadratic programming turned out with the best recognition performance among four comparison methods, its accumulated histogram was much close to that of the ideal case.

V. Conclusion

We propose a filter-driven template matching scheme to recognize one-dimensional tonal sounds and two-dimensional license plate characters. Experiment results demonstrate the proposed method is superior to the conventional methods by direct sampling and average filtering approaches. Our method is robust on recognition against some operations, such as, scaling/amplifying, filtering, translation and noise addition. Furthermore, both the least square estimator and quadratic programming are efficient in recognition of tonal sound. Least square estimator needs less computing time than quadratic programming does. For recognition of license plate characters, quadratic programming has better performance than least square estimator does.

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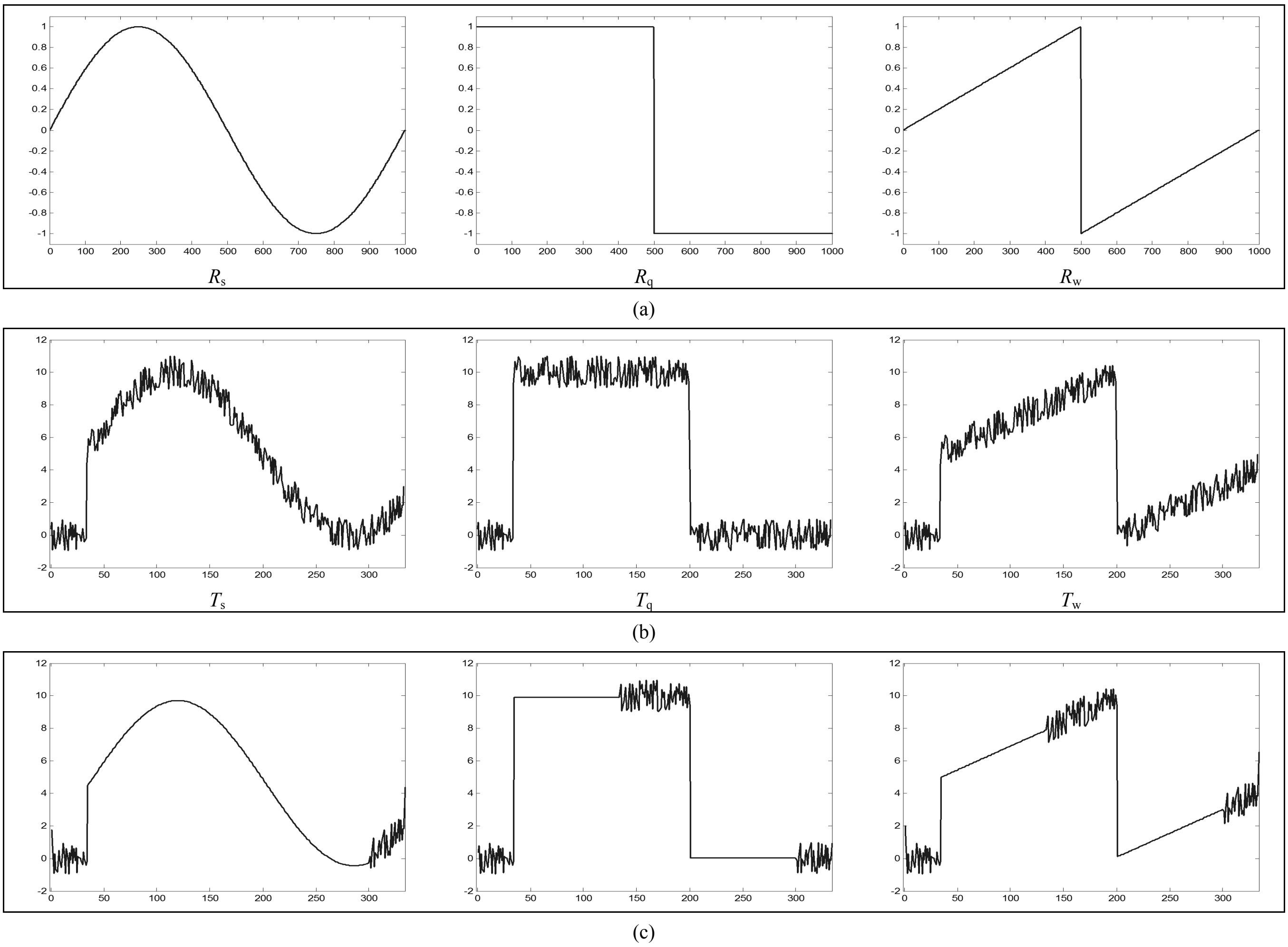

Fig.3. (a) Original reference signals, (b) corrupted signals (query signals), and (c) filtered signals with minimum SSD values

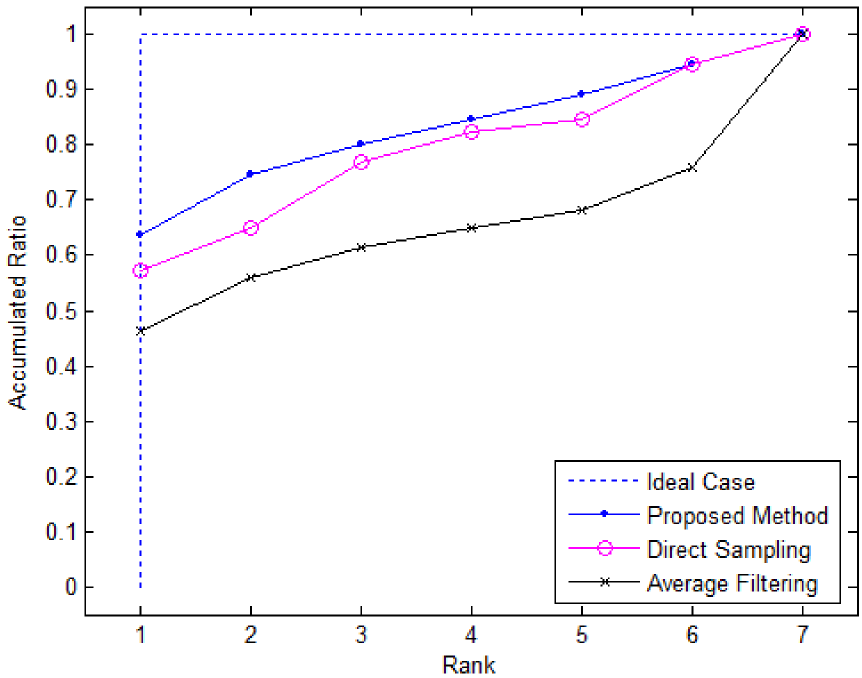

Fig.4. Recognition resultants of seven kinds of tonal sounds using three comparison methods

(a) (b)

Fig.5. (a) Thirty-five reference patterns, and (b) some query patterns.

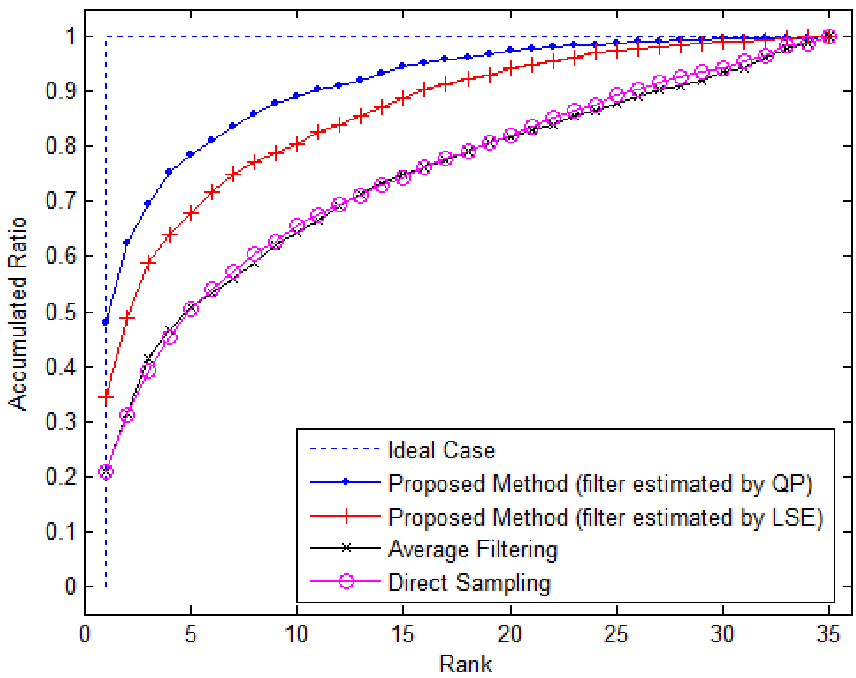

Fig.6. Recognition resultants of thirty-five kinds of license plate characters using four comparison methods