

A new NMR-based metabolomics approach for the diagnosis of biliary tract cancer

He Wen^{1,†}, Sung Soo Yoo^{2,†}, Jinho Kang¹, Hee Goo Kim², Jin-Seok Park², Seok Jeong², Jung Il Lee², Hyuk Nam Kwon¹, Sunmi Kang¹, Don-Haeng Lee^{2,*}, Sunghyoun Park^{1,*}

¹Department of Biochemistry, Inha University Hospital and Center for Advanced Medical Education by BK21 Project, College of Medicine, Inha University, Shinheung-dong, Chung-gu, Incheon 400-712, Republic of Korea; ²Division of Gastroenterology, Department of Internal Medicine, Inha University Hospital and Center for Advanced Medical Education by BK21 Project, College of Medicine, Inha University, Incheon, Republic of Korea

Background & Aims: Biliary tract cancer is highly lethal at presentation, with increasing mortality worldwide. Current diagnostic measures employing multiple criteria such as imaging, cytology, and serum tumor markers are not satisfactory, and a new diagnostic tool is needed. Because bile is a cognate metabolite-rich bio-fluid in the biliary ductal system, we tested a new metabolomic approach to develop an effective diagnostic tool.

Methods: Biles were collected prospectively from patients with cancer ($n = 17$) or benign biliary tract diseases ($n = 21$) with percutaneous or endoscopic methods. Nuclear magnetic resonance spectra (NMR) of these biles were analyzed using orthogonal partial least square discriminant analysis (OPLS-DA).

Results: The metabolomic 2-D score plot showed good separation between cancer and benign groups. The contributing NMR signals were analyzed using a statistical TOCSY approach with verification. The diagnostic performance assessed by leave-one-out analysis exhibited 88% sensitivity and 81% specificity, better than the conventional markers (CEA, CA19-9, and bile cytology).

Conclusion: The NMR-based metabolomics approach provides good performance in discriminating cancer and benign biliary duct diseases. The excellent predictability of the method suggests that it can, at least, increase the currently available diagnostic approaches.

© 2009 European Association for the Study of the Liver. Published by Elsevier B.V. All rights reserved.

Introduction

Biliary tract cancer arises from epithelial cells of the intrahepatic and extrahepatic bile ducts. Although this type of cancer is not very common, it is highly lethal, since most are locally advanced at presentation. Its incidence increases with age, and the mortality is increasing worldwide [1–4]. Patients with biliary tract cancer often present painless jaundice, pruritus, and/or anorexia. Hepatic resection and liver transplantation are the only curative options for this cancer, but the recurrence rate is high.

The diagnosis of biliary tract cancer is usually done based on a combination of radiologic, histological, and tumor marker evidence, because each of these approaches alone has drawbacks. Tissue diagnosis, which could confirm the presence of cancer cells, cannot be generally performed due to tumor location, size, and desmoplastic characteristics [5–7]. For example, obtaining tissues through percutaneous fine needle aspiration is frequently not possible, since many of these tumors are located in the liver hilum amid large vascular structures [8,9].

Serum tumor markers, including carbohydrate antigen 19-9 (CA19-9) and carcinoembryonic antigen (CEA), have been used to diagnose biliary tract cancer [10–12]. These proteins are oncofetal antigens found at high levels in the fetal small intestine and gastrointestinal tumors. CA19-9 is mainly used in pancreatic and biliary tract cancer diagnosis, with sensitivities of about 80% and 60%, respectively [10,11]. However, it can also be elevated in other malignancies such as pancreatic, colon, lung, and breast cancers, and other benign conditions such as pancreatitis, bile stasis, cholangitis, and inflammatory bowel disease. CEA is normally found in embryonic entodermal tissues and fetal gastrointestinal tissues, but also elevated in adult cancers, such as pancreatic, stomach, lung, and hepatobiliary cancers [13]. Therefore, these serum markers alone are not sufficient to diagnose biliary tract cancers, and other benign biliary duct complications can compromise their utility [14].

Bile cytology has been used widely for the diagnosis, because bile can be obtained relatively easily with Percutaneous Transhepatic Cholangiography (PTC) and Endoscopic Retrograde Cholangiopancreatography (ERCP). However, ERCP cytology alone gives a low sensitivity of 35% [15], and additional brushing step was reported to improve the sensitivity [16]. This brush cytology is now the most common tissue sampling technique and it can be

Keywords: Bile; Biliary tract cancer; Metabolomics; Diagnosis.

Received 14 April 2009; received in revised form 27 August 2009; accepted 1 September 2009

* Corresponding authors. Tel.: +82 32 8902548; fax: +82 32 8902549 (D.-H. Lee); Tel.: +82 32 8900935; fax: +82 32 8846726 (S. Park).

E-mail addresses: ldh@inha.ac.kr (D.-H. Lee), spark@inha.ac.kr (S. Park).

† These authors contributed equally to this work.

Abbreviations: NMR, nuclear magnetic resonance spectra; OPLS-DA, orthogonal partial least square discriminant analysis; STOCYSY, statistical total correlation spectroscopy; CA19-9, carbohydrate antigen 19-9; CEA, carcinoembryonic antigen; PTC, percutaneous transhepatic cholangiography; ERCP, endoscopic retrograde cholangiopancreatography; PTBD, percutaneous transhepatic biliary drainage; ENBD, endoscopic nasobiliary drainage.



ELSEVIER

Research Article

performed for most biliary strictures detected by endoscopic cholangiography. Even with the brushing step, the reported sensitivity is still low and variable, with its mean value around 60% [17–20]. Moreover, the additional procedure could increase the risk of infection [21]. Overall, diagnosis of biliary tract cancer, especially, differentiating it from benign clinical conditions, is quite difficult, and new diagnostic approaches are highly needed [22].

Recently, a new “-omics” approach, called metabolomics, has emerged as a promising tool to differentiate individuals in disease or toxic conditions [23]. Compared with other omics approaches, metabolomics deals with smaller molecular metabolites in the body these change depending on the subject's environmental states. It can be applied to any bio-fluid, such as urine, serum, saliva, or bile, and is particularly useful for organs that store or produce small molecular metabolites. Metabolomics can be readily employed for new diagnostic approaches, as first shown in a study with 36 coronary heart disease patients, where it showed its utility as a rapid and non-invasive diagnostic tool with high sensitivity and specificity [23,24]. Metabolomics has subsequently shown promising results in diagnosing several cancers, such as those in breast, ovary, and prostate [25].

Here, we have applied pattern recognition techniques and expert data analysis to NMR spectra of biles taken from individuals with biliary tract cancer or benign biliary tract diseases. The objective of this study was to evaluate the performance of metabolomic diagnosis of biliary tract cancer in comparison with the conventional diagnostic tools including serum tumor markers (CA19-9, CEA) and bile cytology. Our approach gave good distinction between the cancer and benign diseases and better sensitivity and specificity than the other approaches. This metabolomic approach may become a reliable and convenient diagnostic tool for biliary tract cancer.

113 Patients and methods

114 Patients

115 Informed consent was obtained from every patient enrolled in this study and
116 the study protocol conforms to the ethical guidelines of the 1975 Declaration of Hel-
117 sinki. The study was approved before initiation by the Institutional Review Board
118 at the Inha University Medical School and Hospital.

119 We prospectively obtained bile samples from patients with biliary tract cancer
120 and benign biliary tract diseases at the Inha University Hospital (Incheon,
121 Korea) between January, 2006, and August, 2007. Patients with severe biliary sep-
122 sis were excluded from this study. This study included 17 patients with biliary
123 tract cancer and 21 patients with benign biliary tract disease (Table 1). The
124 patient groups were not matched on gender, age or disease stages to maximize
125 patient diversity. There were no exclusion criteria except for biliary sepsis, which
126 severely distorts metabolite profiles but can be easily diagnosed with other meth-
127 ods as reported previously [26].

128 Assays and bile cytology

129 Serum CA19-9 and CEA were assayed with an immunoradiometric method and a
130 commercially available ELSA-CA19-9 and ELSA2-CEA (Cisbio International, Bed-
131 ford, MA). For patients with biliary tract cancer, routine diagnostic procedures
132 included abdominal CT scans or ultrasound. Upon identifying a duct stricture,
133 we performed percutaneous transhepatic biliary drainage (PTBD) or endoscopic
134 nasobiliary drainage (ENBD) as needed.

135 Sample collection

136 Bile samples were collected by PTBD, ENBD or during operation. The collected
137 biles were frozen at -80 °C immediately and freeze-dried *in vacuo*. Ten milligrams
138 of the dried samples were re-solubilized into 500 µl of a D₂O + CD₃OD mixture

Table 1. Clinical patient characteristics.

	Biliary tract cancer	Benign biliary tract disease ^f
<i>Clinical parameters</i>	(n = 17)	(n = 21)
Gender (M:F)	4.7:1	1.3:1
Age, years ^a	70.4 ± 10.6	59.4 ± 15.5
<i>Methods of bile sampling</i>		
PTBD [†]	13	2
ENBD [†]	3	14
Operation	1	5
<i>Cancer stages^b</i>		
I	Ia: 5, Ib: 2	–
II	IIa: 3, IIb: 2	–
III	IIIa: 1, IIIb: 2, 11 Ic: 2	–
<i>Diagnosis of cancer^c</i>		
Operation ^d	5	–
Operation and Bile cytologie ^d	4	–
Bile cytologie ^d	3	–
Clinical and radiological ^e	5	–

Out of 17 cancer patients, 9 patients were diagnosed by operation (Operation (5) + Operation and Bile cytologie(4)). In addition, three un-operated patients showed positive in cancer cells in the drained bile. Therefore, total of 12 patients (71%) were diagnosed either by operation or bile cytologie. Overall, the sensitivity of the bile cytologie was 41%. For the rest of the cancer patients (five, 29%), histological examination (bile cytologie, brushing cytologie, guided fine needle aspiration) could not detect cholangiocarcinoma. However, radiological (cholangiography and abdominal CT), and clinical (obstructive jaundice, weight loss, abdominal pain or incidental abdominal mass detection) evidence justified the diagnosis of cholangiocarcinoma. Moreover, all of the patients died of cancer progression within one year of diagnosis, which gave additional support to our diagnosis.

[†] PTBD, Percutaneous transhepatic biliary drainage; ENBD, Endoscopic nasobiliary drainage.

^a Values expressed as the mean + SD (range).

^b According to American joint committee on cancer staging manual (2002, 6th Edition, Springer).

^c All of the patients died of cancer progression within one year of diagnosis.

^d These represent the gold standard of the biliary duct cancer diagnosis.

^e Radiological evidence includes cholangiography and abdominal CT. Clinical evidence includes obstructive jaundice, weight loss, abdominal pain or incidental abdominal mass detection.

^f One cancer patient had been treated with intrahepatic duct stone before the cholangiocarcinoma.

139 containing 10 mM sodium phosphate (pH 6.0). Insoluble material was removed
140 by centrifugation, and 0.025% TSP was added for chemical shift referencing and
141 normalization.

142 NMR measurements

143 All spectra were obtained by an NMR spectrometer (Bruker Biospin Avance 500)
144 operating at a proton NMR frequency of 500.13 MHz. The acquisition parameters
145 were essentially the same as previously reported [27,28]. The time domain data
146 were Fourier transformed, phase corrected, and baseline corrected manually. This
147 study made use of the NMR facility at Korea Basic Science Institute, which is sup-
148 ported by Bio-MR Research Program of the Korean Ministry of Science and Tech-
149 nology (E28080).

150 Metabolomics data analysis

151 To reduce the complexity of the NMR data for pattern recognition, the spectra
152 were binned with 0.04 ppm width using an in-house Perl program. The signals
153 were normalized against total integration values, and then, 0.025% TSP signal.
154 The water and methanol regions were excluded. The numeric data were imported
155 into statistical software. Matlab (MathWorks, Natick, MA), SIMCA-P version 11.0
156 (Umetrics, Sweden), Chenomx (Spectral database; Edmonton, Alberta, Canada)
157 and Excel (Microsoft, Seattle, WA) programs were used for data analysis. Ortho-
158 gonal projections to latent structure-discriminant analysis (OPLS-DA) were per-
159 formed to distinguish cancer and benign patient groups. The statistical
160 validation was performed using “Y-scrambling” validation, where the class mem-

161 bership was shuffled 200 times randomly, and the resulting Q^2 and R^2 values were
 162 calculated. Prediction of the unknown samples was carried out by leave-one-out
 163 analysis, as reported previously [29]. The conceptual explanation of these meth-
 164 ods is given in Supplementary material S4.

165 Results

166 Patient characteristics

167 The biliary tract cancer group included 13 Klatskin tumors, two
 168 CBD cancers, one gallbladder cancer, and one intrahepatic chol-
 169 angiocarcinoma. There were 17 bile duct stones, two benign bili-
 170 ary strictures, one choledochal cyst, and one other disease in the
 171 benign biliary tract group. Patient characteristics of the two
 172 groups were different because of the epidemiology of biliary tract
 173 cancer (Table 1). Bile sampling was also different between the
 174 two groups because treatment options for the two groups
 175 differed.

176 NMR spectra and multivariate analysis

177 We obtained NMR spectra of bile samples from both patient
 178 groups. The general spectral features were similar, with large
 179 peaks in the aliphatic region (2.3–0.8 ppm) corresponding to
 180 the bile acids, cholesterol, fatty acids, and other lipid compo-
 181 nents, present abundantly in bile (Fig. 1). To analyze the NMR
 182 data holistically and to establish the prediction model for biliary
 183 tract cancer, we applied OPLS-DA multivariate analysis to the
 184 NMR data. The results revealed that analysis with signals upfield
 185 of 6.0 ppm gave better separation (data not shown), probably due
 186 to the aliphatic nature of the bile components. Therefore, we per-
 187 formed the subsequent analysis with the 0–6.0 ppm region sig-
 188 nal. The OPLS-DA distinction model was obtained using one
 189 predictive (P_p) and four orthogonal components (P_o) (Fig. 2).
 190 The majority of the normal and cancer samples appear clustered
 191 in their respective regions with only a few overlaps between
 192 them. The model featured an overall goodness of fit, $R^2(Y)$, of
 193 95% and an overall cross-validation coefficient, $Q^2(Y)$, of 91%.
 194 Out of the overall $R^2(X)$ value of 0.87, 60% was structured but
 195 uncorrelated to the response, and 27% was predictive. These
 196 results show that there is considerable variation within each
 197 group, but that our model can reliably differentiate between
 198 them, even with large structured noise.

199 Statistical TOCSY analysis

200 With the efficient separation of the cancer and benign groups, we
 201 further identified the variables responsible for the classification
 202 rules. We utilized statistical total correlation spectroscopy (STO-
 203 CSY), which can show the modeled correlation ($P(\text{corr})_p$) as NMR
 204 lines, enabling straightforward interpretation of the variable con-
 205 tributions [27,30,31]. The STOCYSY plot (Fig. 3) shows that impor-
 206 tant contributions for the separation come from signals at 1.50
 207 (1), 1.06 (2), and 3.70 (3) ppm, which correspond to $-\text{CH}_2-$, $-\text{CH}_3-$,
 208 and $-\text{CH}_n-\text{OR}$ moieties that are common in bile acids.
 209 Therefore, differences in the bile acid composition are impor-
 210 tantly related to the class differentiation. However, the $P(\text{corr})_p$
 211 values indicate that variations in these signals are not entirely
 212 responsible for the class difference. This is not very surprising,
 213 considering a previous report on coronary heart disease [23].
 214 There, only 20–30% of the variance of the most important vari-

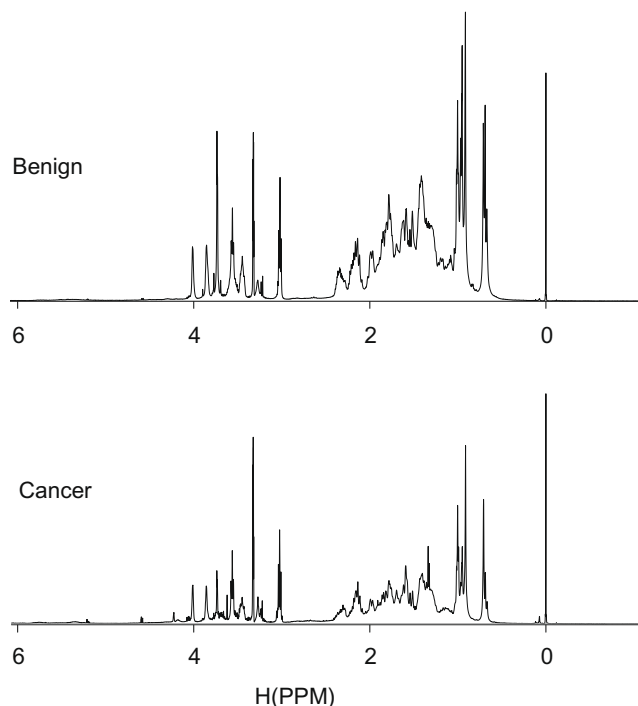


Fig. 1. Representative 500 MHz ^1H -NMR spectra of bile samples from a benign biliary tract disease patient (top) and a biliary tract cancer patient (bottom). The spectra were taken for samples in 500 μl of $\text{D}_2\text{O} + \text{CD}_3\text{OD}$ mixture containing 10 mM sodium phosphate (pH 6.0) and 0.025% TSP as a chemical shift reference.

ables was related to the heart disease risk, but very high sensitiv-
 ity and specificity were still obtained. Therefore, the remaining
 variations in our case should result from subtle individual chemi-
 cal differences in bile acids, such as the position of the double
 bonds and bile-metabolite conjugation.

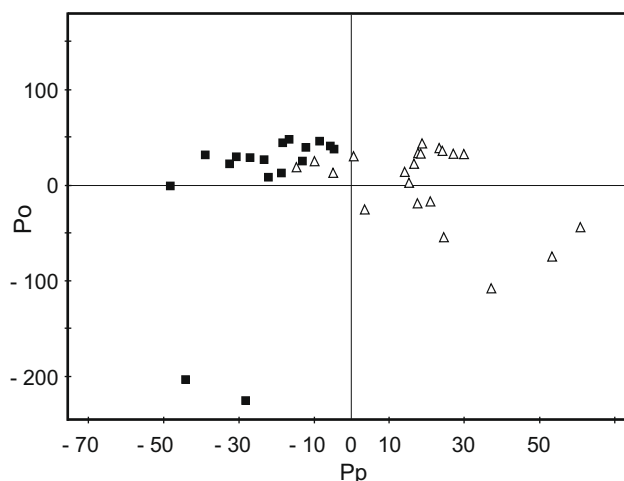


Fig. 2. Orthogonal projections to latent structure-discriminant analysis (OPLS-DA) score plot of benign and cancer samples. Open triangle: Benign samples; Filled box: Cancer samples. The model was obtained using one predictive and four orthogonal component, with $R^2(Y)$ of 95% and $Q^2(Y)$ of 91%. P_p represents the predictive component and P_o represents the orthogonal component.

Research Article

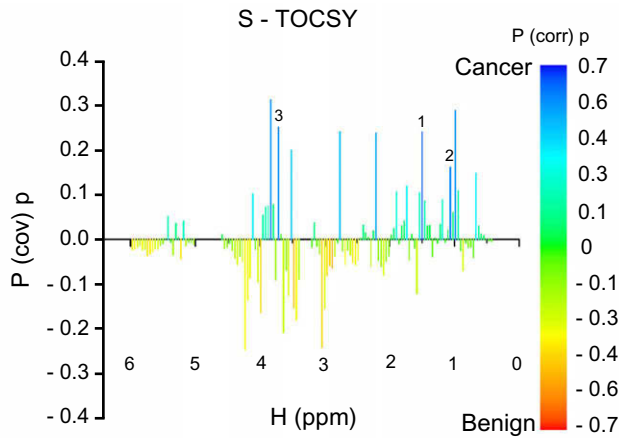


Fig. 3. Variable contributions from statistical total correlation spectroscopy (STOCSY). The color scale on the right indicates $P(\text{corr})_p$. The $P(\text{cov})_p$ represents the modeled covariance and $P(\text{corr})_p$ represents the modeled correlation. Peaks with labels are mentioned in the text (1: 1.50 ppm, 2: 1.06 ppm, 3: 3.70 ppm).

Statistical validation

The separation result of the cancer and normal patients was subjected to “Y-scrambling” statistical validation to test the possibility of chance correlation. We randomly permuted the Y-variable (cancer or benign group designation), re-built the statistical model, and observed the trends of the predictive power and goodness of fit at each step. Two hundred rounds of such reshuffling gave coherent decreases in both parameters and the extrapolated value of the Q^2 of -0.3 (Fig. 4), which shows that the separation model is statistically sound, and that its high predictability is not due to over-fitting of the data. Although the current study may not cover all the possible variations in the patients, such as the bile duct obstruction time, we believe our validation through randomization of the Y-variable suggests that those variations should be orthogonal to, and thus not be a major factor for our differentiation between the cancer and normal groups. Unrelated variations were most likely partitioned into the orthogonal components of the prediction model and, thus, should not affect the predictability.

Among the unrelated variations, gender and age could provide a large source of variation that may affect the differentiation. Therefore, we analyzed the patient data in subgroups that are

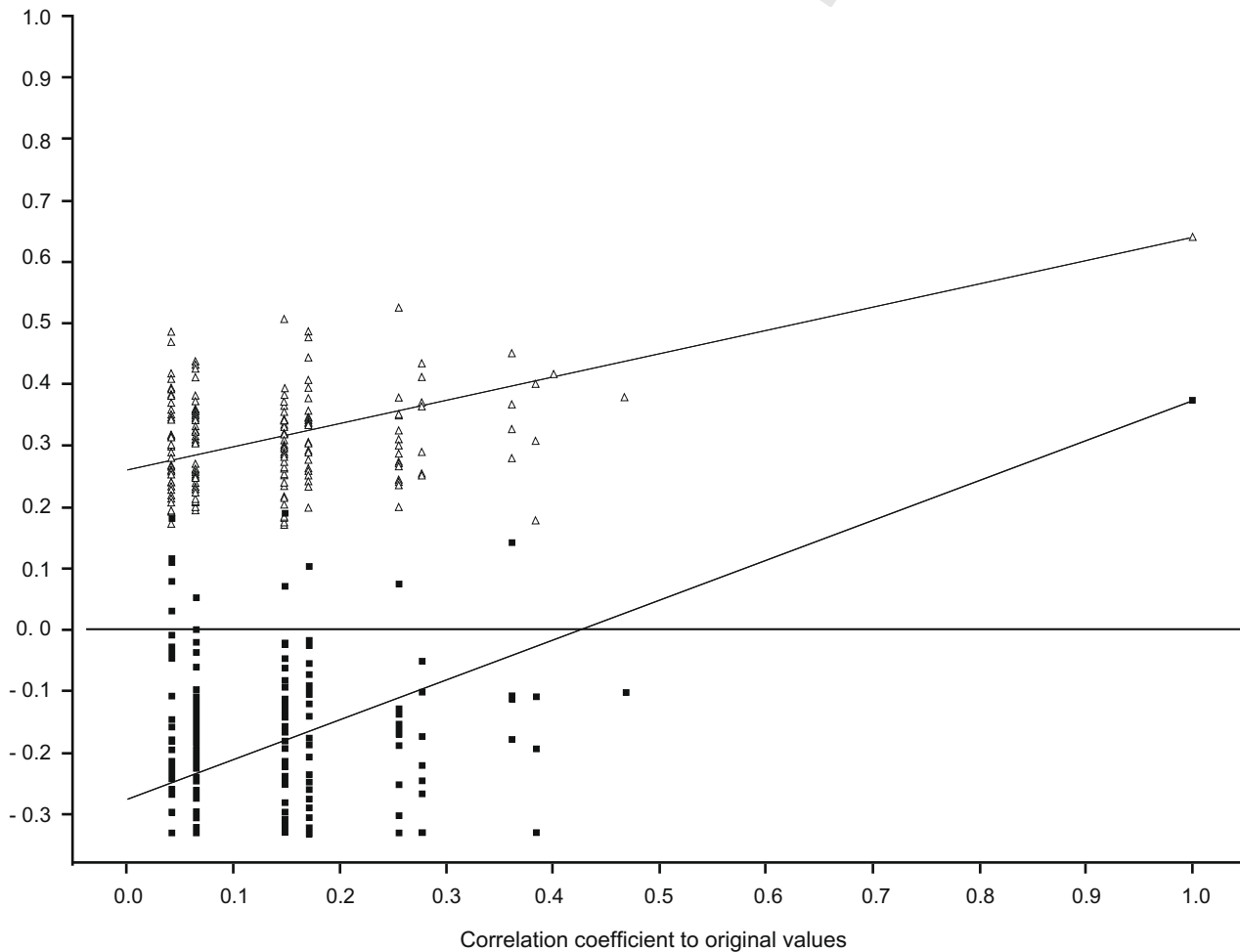


Fig. 4. Statistical validation of the OPLS-DA analysis result by “Y-scrambling”. Two hundred permutations were performed, and the resulting R^2 and Q^2 values were plotted. Open triangle: R^2 ; Filled square: Q^2 . The solid line represents the regression line for R^2 and the dashed line for Q^2 .

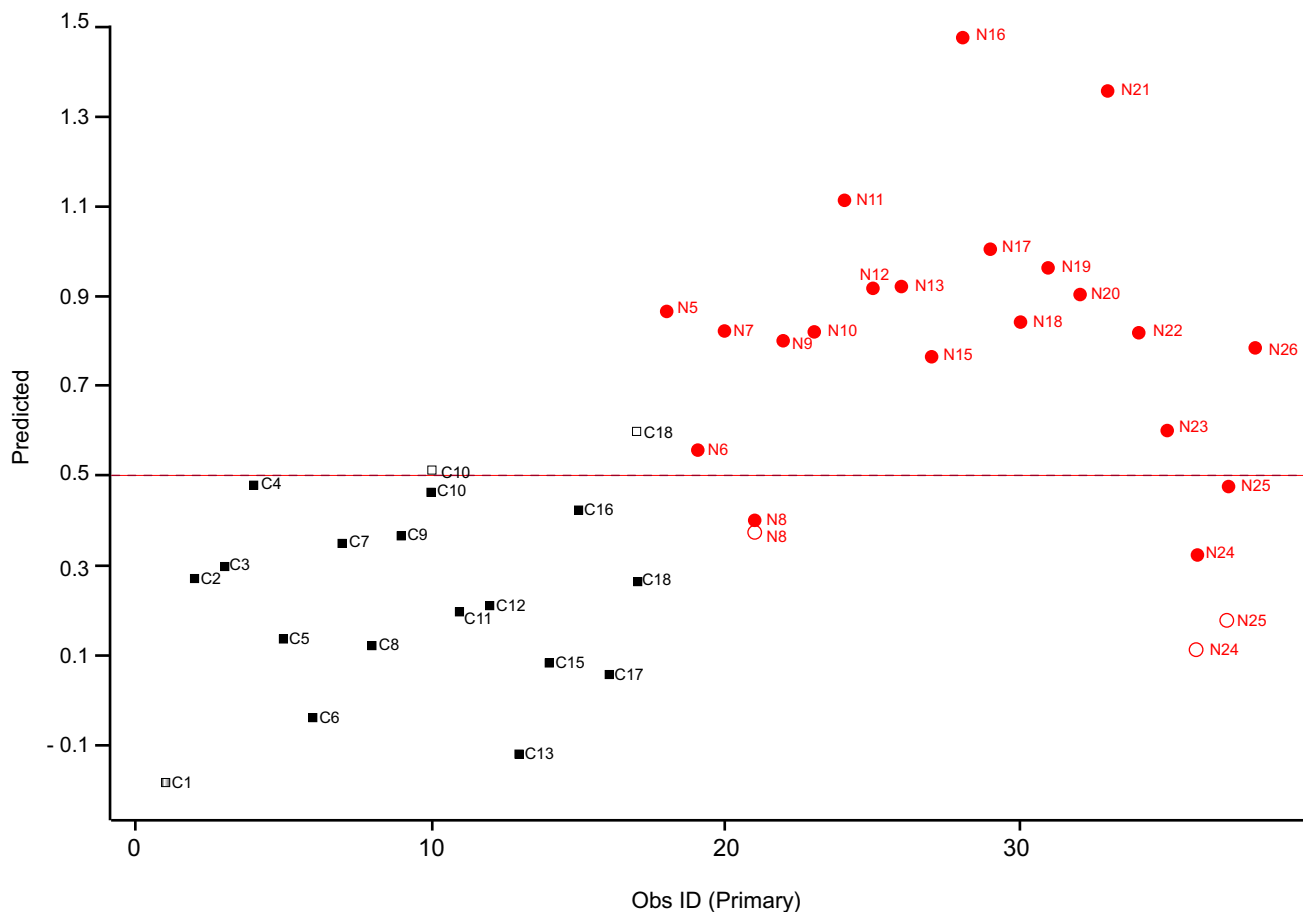


Fig. 5. Prediction of cancer and benign patients using leave-one-out analysis. One patient sample (unknown) was left-out at a time and an OPLS-DA prediction model was constructed with the rest of the data. The class membership of the left-out samples was predicted using an *a priori* cut-off value of 0.5 (dashed line) [23]. Cancer samples: black box; Benign samples: Red circle. The Y values of the filled symbols are from the analysis using the entire dataset. In the case of mis-classified samples, the predicted Y values from the leave-one-out analysis are also shown as open boxes (cancer patients) and open circles (normal patients).

241 not affected by these biases. First, we performed the differentiation
 242 with only male patients, as the cancer group is primarily male and
 243 the benign group has relatively even distribution. The actual result
 244 (see Supplementary Fig. S1A) exhibited very similar differentiation
 245 as our original model with all the patients (see Fig. 2), which con-
 246 firms that our original differentiation is not based on the gender. If
 247 the original model had been influenced by the gender, the male-
 248 only analysis should have given much poorer, or even no, discrim-
 249 ination between the cancer and benign groups. We also tested the
 250 influence of age in our model. In separate analyses with younger
 251 (see Supplementary Fig. S1B) and older groups (see Supplementary
 252 Fig. S1C), the differentiation of cancer and benign groups were even
 253 better than the one with all the patients (see Fig. 2). As stated
 254 above, if our original model had been influenced mainly by age,
 255 the differentiation should have been much worse in each sub-
 256 group. These results again confirm the validity of our OPLS-DA
 257 approach which can effectively exclude these possible confound-
 258 ing factors in differentiating the groups based on the feature of
 259 interest (cancer status, in our case).

260 *Prediction and diagnostic performance test*

261 To estimate the actual performance of our OPLS-DA model in
 262 diagnosing biliary tract cancer, we performed a leave-one-out

263 predictive test. For this, we left-out one patient sample at a time
 264 and constructed the OPLS-DA prediction model with the rest of
 265 the data (a training set). The prediction model was constructed
 266 with the same number of predictive and orthogonal components
 267 as the original OPLS-DA classification model. The class member-
 268 ship of the left-out sample was predicted using an *a priori* cut-
 269 off value of 0.5. This procedure was repeated until each and every
 270 sample had been tested once. Of the 21 benign disease samples,
 271 18 were predicted correctly as benign, and of the 17 cancer sam-
 272 ples, 15 were predicted correctly as cancer (Fig. 5). Therefore, our
 273 OPLS-DA metabolomics prediction model exhibited a sensitivity
 274 of 88% and a specificity of 81% for biliary tract cancer diagnosis,
 275 which is significantly better than conventional serum markers
 276 or cytology (Table 2).

277 **Discussion**

278 Biliary tract cancer is highly lethal and only surgical excision of
 279 the tumor can improve survival [32–35]. However, biliary tract
 280 cancer is often presented locally advanced, and the majority of
 281 the patients are elderly, with critical co-morbidity which
 282 increases the risk of operation. In this respect, it has been sug-
 283 gested that neither more advanced surgical techniques nor radi-

Research Article

Table 2. Comparison of the diagnostic performance between conventional and metabolomic.

Criteria [Reference]	CA19-9** [22]	CEA† [9]	Bile cytology [15,20]	Metabolomics [current study]
Sensitivity	81% (73%)	20% (68%)	41% (35–61**%)	88%
Specificity	53% (63%)	100% (82%)	N/A	81%

* The numbers indicate the values obtained from the patients enrolled in the current study. The numbers in the parenthesis are from the literature.

** Cut-off value of >37 U/mL (both reference and our study).

† Cut-off value of >5.2 ng/mL in primary sclerosing cholangitis patients and cut-off value of 6.0 ng/mL in our study.

** 61% was obtained using brush cytology.

ation therapy is likely to improve survival [36]. Therefore, currently, efforts are being directed to prevention and reliable detection. However, current diagnostic tools, such as serum tumor markers and bile cytology, have limited utility for differentiating cancer and benign diseases, and new diagnostic methods are highly needed.

Here, we applied a metabolomics approach to biles obtained directly from patients in order to assess its accuracy and reliability in diagnosing biliary tract cancer. Our approach showed better performance in terms of both specificity and sensitivity than conventional data obtained from literature and our own patients (Table 2). Although CEA showed perfect specificity for our patients, its utility was significantly compromised due to its poor sensitivity. In general, sensitivity is more important than specificity in serious diseases such as cancer. Bile cytology, in theory, can deliver perfect specificity, as it directly observes cancer cells in the samples, but its reported sensitivity is rather poor to range between 35% and 40% [15,37]. We also obtained 41% sensitivity using bile cytology for our patients. Although brushing has been shown to increase cytology sensitivity by about 20% [17–20], it requires additional invasive steps such as ERCP or EST, which could increase the risk of pancreatitis [21]. The final sensitivity of brush cytology is still about 60%, significantly lower than our metabolomics results. Our metabolomics approach gave high values for both sensitivity and specificity. Therefore, we believe that the metabolomic diagnosis may be more clinically useful than conventional techniques in biliary tract cancer diagnosis. Obviously, as with any other new diagnostic approaches, there are limitations to our study. One such possibility is the effects of biliary infection without clinical evidence of sepsis on the metabolic profiles. This potential confounding factor, though, can be diagnosed by culture or PCR, and therefore, may be an interesting subject for later studies.

To get deeper insights into the metabolic difference, we analyzed our data with targeted metabolic profiling for four metabolites involved importantly in energy metabolic pathways: choline, lactate, citrate and glucose. We used student's independent *t*-test to see if the contents of these metabolites are statistically different between cancer and benign groups (see Supplementary Fig. S2). While choline ($p > 0.85$), lactate ($p > 0.79$), and glucose ($p > 0.24$) did not show any relevant differences, citrate level was statistically higher in cancer groups ($p < 0.05$). The higher content of citrate is interesting, as it is the starting molecule of the TCA cycle, the hallmark of the aerobic energy metabolism. Citrate is formed through a condensation reaction between oxaloacetate and acetyl CoA. The latter is also the precursor of the cholesterol which is metabolized into bile acids. The higher level of citrate in the cancer group might result from the low dependence of the cancer cells on the aerobic

energy metabolism consuming citrate in the TCA cycle, consistent with the Warburg effect in cancer cells. High level of citrate is expected to affect the concentration of acetyl CoA, its immediate precursor, which in turn can affect the bile acid formation. As citrate also has $-CH_2-$ group, this is consistent with our initial suggestion on contributing signals. Although confirmation of the above will require detailed flux analysis of all the involved pathways, our metabolomic data provide an interesting initial evidence for the link between the energy metabolism and bile acid compositions in the cancer group.

In addition to our main goal of differentiating cancer and benign patients, we also tested if our approach can differentiate the various stages of the biliary duct cancer. Although individual differentiation of stages I, II, and III were not satisfactory (data not shown), we obtained a good separation between stages I and II combined against stage III (see Supplementary Fig. S3). Although the number of patients is not large for each group, these data suggest that it may be possible to differentiate between relatively early (I and II) and later stage biliary duct cancers with our metabolomic approach.

It should be noted that our metabolomics approach is “non-invasive”, as it uses bile that had been drained for therapeutic purposes and required no separate collection steps. In contrast, brush bile cytology requires additional steps, and serum markers require blood drawing. This fact also alleviates ethical problems, the inconvenience of additional visits, or pain for sample collection for patients, providing a more convenient option.

An efficient diagnostic method is best developed with tissues or bio-fluids that are cognate to the organs of interest. For example, urine metabolites have been used to predict kidney cancer or allograft rejection [29,38]. Here, we used bile for biliary duct cancer diagnosis. Bile passes through the biliary duct before being secreted into the intestine, during which time it has direct contact with any surrounding cancer tissue. Especially in obstructive bile duct diseases, such as those targeted in this study, bile stays in the ducts for a long time, thus likely reflecting differences in the ductal epithelial cells. Conventional serum markers, such as CA-19-9 and CEA are detected from serum and, therefore, could reflect changes in other tissues, including colon or pancreatic cancers. Bile cytology, although using bile, may not always be able to retrieve cancer cells from the tissue, resulting in low sensitivity. Therefore, bile metabolomics seems more theoretically relevant for the biliary tract cancer diagnosis than those approaches.

Currently, biliary tract cancer is diagnosed by multiple criteria based on computerized tomography, magnetic resonance imaging, bile cytology, endoscopic ultrasonography, serum markers, and positron emission tomography. Our study shows that a metabolomics approach, by itself, can differentiate biliary tract cancer from benign diseases with high reliability. To the best of our knowledge, this study is the first report of a metabolomics diagnostic approach in the human hepatobiliary system outperforming other conventional clinical criteria. A study with larger patient groups and standardized protocols could eventually lead to a dependable diagnostic tool for biliary tract cancer.

Acknowledgements

The authors who have taken part in this study declared that they do not have anything to declare regarding funding from industry or conflict of interest with respect to this manuscript.

392 **Appendix A. Supplementary data**

393 Supplementary data associated with this article can be found, in
394 the online version, at doi:10.1016/j.jhep.2009.11.002.

395 **References**

- 396 [1] Patel T. Increasing incidence and mortality of primary intrahepatic cholan-
397 giocarcinoma in the United States. *Hepatology* 2001;33:1353–1357.
- 398 [2] El Rassi ZE, Partensky C, Scoazec JY, Henry L, Lombard-Bohas C, Maddern G.
399 Peripheral cholangiocarcinoma: presentation, diagnosis, pathology and
400 management. *Eur J Surg Oncol* 1999;25:375–380.
- 401 [3] Taylor-Robinson SD, Toledano MB, Arora S, Keegan TJ, Hargreaves S, Beck A,
402 et al. Increase in mortality rates from intrahepatic cholangiocarcinoma in
403 England and Wales 1968–1998. *Gut* 2001;48:816–820.
- 404 [4] Patel T. Worldwide trends in mortality from biliary tract malignancies. *BMC*
405 *Cancer* 2002;2:10.
- 406 [5] Ohtsuka M, Ito H, Kimura F, Shimizu H, Togawa A, Yoshidome H, et al. Results
407 of surgical treatment for intrahepatic cholangiocarcinoma and clinicopatho-
408 logical factors influencing survival. *Br J Surg* 2002;89:1525–1531.
- 409 [6] Ueno N, Sano T, Kanamaru T, Tanaka K, Nishihara T, Idei Y, et al.
410 Adenosquamous cell carcinoma arising from the papilla major. *Oncol Rep*
411 2002;9:317–320.
- 412 [7] Saito M, Hige S, Takeda H, Tomaru U, Shibata M, Asaka M. Combined
413 hepatocellular carcinoma and cholangiocarcinoma growing into the com-
414 mon bile duct. *J Gastroenterol* 2001;36:842–847.
- 415 [8] Matsumoto A, Imamura M, Akagi Y, Kaibara A, Ohkita A, Mizobe T, et al. A
416 case report of disseminated recurrence of inferior bile duct carcinoma in
417 PTCd fistula. *Kurume Med J* 2002;49:71–75.
- 418 [9] Siqueira E, Schoen RE, Silverman W, Martin J, Rabinovitz M, Weissfeld JL,
419 et al. Detecting cholangiocarcinoma in patients with primary sclerosing
420 cholangitis. *Gastrointest Endosc* 2002;56:40–47.
- 421 [10] Steinberg W. The clinical utility of the CA 19-9 tumor-associated antigen.
422 *Am J Gastroenterol* 1990;85:350–355.
- 423 [11] Perkins GL, Slater ED, Sanders GK, Prichard JG. Serum tumor markers. *Am*
424 *Fam Physician* 2003;68:1075–1082.
- 425 [12] Qin XL, Wang ZR, Shi JS, Lu M, Wang L, He QR. Utility of serum CA19-9 in
426 diagnosis of cholangiocarcinoma: in comparison with CEA. *World J Gastro-*
427 *enterol* 2004;10:427–432.
- 428 [13] Carpelan-Holmstrom M, Louhimo J, Stenman UH, Alftan H, Haglund C. CEA,
429 CA 19-9 and CA 72-4 improve the diagnostic accuracy in gastrointestinal
430 cancers. *Anticancer Res* 2002;22:2311–2316.
- 431 [14] Bjornsson E, Kilander A, Olsson R. CA 19-9 and CEA are unreliable markers
432 for cholangiocarcinoma in patients with primary sclerosing cholangitis.
433 *Liver* 1999;19:501–508.
- 434 [15] Davidson B, Varsamidakis N, Dooley J, Deery A, Dick R, Kurzawinski T, et al.
435 Value of exfoliative cytology for investigating bile duct strictures. *Gut*
436 1992;33:1408–1411.
- 437 [16] Osnes M, Serck-Hanssen A, Myren J. Endoscopic retrograde brush cytology
438 (ERBC) of the biliary and pancreatic ducts. *Scand J Gastroenterol*
439 1975;10:829–831.
- 440 [17] de Bellis M, Fogel EL, Sherman S, Watkins JL, Chappo J, Younger C, et al.
441 Influence of stricture dilation and repeat brushing on the cancer detection
442 rate of brush cytology in the evaluation of malignant biliary obstruction.
443 *Gastrointest Endosc* 2003;58:176–182.
- 444 [18] Kurzawinski T, Deery A, Davidson BR. Diagnostic value of cytology for biliary
445 stricture. *Br J Surg* 1993;80:414–421.
- 446 [19] Logrono R, Kurtycz DF, Molina CP, Trivedi VA, Wong JY, Block KP. Analysis of
447 false-negative diagnoses on endoscopic brush cytology of biliary and
448 pancreatic duct strictures: the experience at 2 university hospitals. *Arch*
449 *Pathol Lab Med* 2000;124:387–392.
- [20] Mahmoudi N, Enns R, Amar J, AlAli J, Lam E, Telford J. Biliary brush cytology:
factors associated with positive yields on biliary brush cytology. *World J*
Gastroenterol 2008;14:569–573.
- [21] Vandervoort J, Soetikno RM, Montes H, Lichtenstein DR, Van Dam J,
Ruymann FW, et al. Accuracy and complication rate of brush cytology from
bile duct versus pancreatic duct. *Gastrointest Endosc* 1999;49:322–327.
- [22] Kim HJ, Kim MH, Myung SJ, Lim BC, Park ET, Yoo KS, et al. A new strategy for
the application of CA19-9 in the differentiation of pancreaticobiliary cancer:
analysis using a receiver operating characteristic curve. *Am J Gastroenterol*
1999;94:1941–1946.
- [23] Brindle JT, Antti H, Holmes E, Tranter G, Nicholson JK, Bethell HW, et al. Rapid
and noninvasive diagnosis of the presence and severity of coronary heart
disease using ¹H-NMR-based metabolomics. *Nat Med* 2002;8:1439–1444.
- [24] Goodacre R, Vaidyanathan S, Dunn WB, Harrigan GG, Kell DB. Metabolomics
by numbers: acquiring and understanding global metabolite data. *Trends*
Biotechnol 2004;22:245–252.
- [25] Claudino WM, Quattrone A, Biganzoli L, Pestrin M, Bertini I, Di Leo A.
Metabolomics: available results, current research projects in breast cancer,
and future applications. *J Clin Oncol* 2007;25:2840–2846.
- [26] Park SY, Park CH, Cho SB, Yoon KW, Lee WS, Kim HS, et al. The safety and
effectiveness of endoscopic biliary decompression by plastic stent place-
ment in acute suppurative cholangitis compared with nasobiliary drainage.
Gastrointest Endosc 2008;68:1076–1080.
- [27] Kang J, Choi MY, Kang S, Kwon HN, Wen H, Lee CH, et al. Application of a ¹H
nuclear magnetic resonance (NMR) metabolomics approach combined with
orthogonal projections to latent structure-discriminant analysis as an
efficient tool for discriminating between Korean and Chinese herbal
medicines. *J Agric Food Chem* 2008;56:11589–11595.
- [28] Kang J, Lee S, Kang S, Kwon HN, Park JH, Kwon SW, et al. NMR-based
metabolomics approach for the differentiation of ginseng (Panax ginseng)
roots from different origins. *Arch Pharm Res* 2008;31:330–336.
- [29] Kim K, Aronov P, Zakharkin SO, Anderson D, Perroud B, Thompson IM, et al.
Urine metabolomic analysis for kidney cancer detection and biomarker
discovery. *Mol Cell Proteomics* 2009;8:558–570.
- [30] Wiklund S, Johansson E, Sjöstrom L, Mellerowicz EJ, Edlund U, Shockcor JP,
et al. Visualization of GC/TOF-MS-based metabolomics data for identifica-
tion of biochemically interesting compounds using OPLS class models. *Anal*
Chem 2008;80:115–122.
- [31] Cloarec O, Dumas ME, Craig A, Barton RH, Trygg J, Hudson J, et al. Statistical
total correlation spectroscopy: an exploratory approach for latent biomarker
identification from metabolic ¹H NMR data sets. *Anal Chem* 2005;77:
1282–1289.
- [32] Nakeeb A, Pitt HA, Sohn TA, Coleman J, Abrams RA, Piantadosi S, et al.
Cholangiocarcinoma: a spectrum of intrahepatic, perihilar, and distal
tumors. *Ann Surg* 1996;224:463–473, discussion 473–465.
- [33] Henson DE, Albores-Saavedra J, Corle D. Carcinoma of the gallbladder:
histologic types, stage of disease, grade, and survival rates. *Cancer*
1992;70:1493–1497.
- [34] Henson DE, Albores-Saavedra J, Corle D. Carcinoma of the extrahepatic bile
ducts: histologic types, stage of disease, grade, and survival rates. *Cancer*
1992;70:1498–1501.
- [35] Farley DR, Weaver AL, Nagorney DM. “Natural history” of unresected
cholangiocarcinoma: patient outcome after noncurative intervention. *Mayo*
Clin Proc 1995;70:425–429.
- [36] de Groen PC, Gores GJ, LaRusso NF, Gunderson LL, Nagorney DM. Biliary tract
cancers. *N Engl J Med* 1999;341:1368–1378.
- [37] Park SW, Song SY, Chung JB, Jung BG, Moon YM, Kang JK, et al. Combined
endoscopic transpapillary biopsy and exfoliative cytology for the diagnosis
of bile duct cancer. *Korean J Gastrointest Endosc* 1999;19:588–596.
- [38] Wang JN, Zhou Y, Zhu TY, Wang X, Guo YL. Prediction of acute cellular renal
allograft rejection by urinary metabolomics using MALDI-FTMS. *J Proteome*
Res 2008;7:3597–3601.