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Forecasting the quality of water-suppressed ^1H MR spectra based on a single-shot water scan

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ABSTRACT

Purpose: To investigate whether an initial non-water-suppressed acquisition that provides information about the signal-to-noise ratio and linewidth is enough to forecast the maximally achievable final spectral quality and thus inform the operator whether the foreseen number of averages and achieved field homogeneity is adequate.

Methods: A large range of spectra with varying signal-to-noise and linewidth was simulated and fitted with popular fitting programs to determine the dependence of fitting errors on linewidth and signal-to-noise. A tool to forecast variance based on a single acquisition was developed and its performance evaluated on simulated and in vivo data obtained at 3 T from various brain regions and acquisition settings.

Results: A strong correlation to real uncertainties in estimated metabolite contents was found for the forecast values and the Cramer-Rao lower bounds obtained from the water-suppressed spectra.

Conclusion: It appears to be possible to forecast the best-case errors associated with specific metabolites to be found in model fits of water-suppressed spectra based on a single water scan. Thus, non-specialist operators will be able to judge ahead of time whether the planned acquisition can possibly be of sufficient quality to answer the targeted clinical question or whether it needs more averages or improved shimming.

Keywords: MR spectroscopy; brain; quantification error; SNR, LW, quality

List of Abbreviations

Asp, Aspartate

Cho, Choline

Cho_{tot}, total Choline (GPC + PCho)

Cr, Creatine

Cr_{tot}, total creatine (Cr + PCr)

GABA, γ -aminobutyric acid

Glc, Glucose

Gln, Glutamine

Glu, Glutamate

Glx, Glutamate + Glutamine

GPC, Glycerophosphocholine

GSH, Glutathione

Gly, Glycine

HLSVD, Hankel-Lanczos Singular Value

Decomposition

jMRUI, Java version of the magnetic resonance user interface

Lac, Lactate

ml, Myo-inositol

ml_{tot}, Myo-inositol + Glycine

NAA, N-acetylaspartate

NAAG, N-acetylaspartyl-glutamate

NAA_{tot}, total NAA (NAA + NAAG)

nWS, Non-water-suppressed

PCho, Phosphocholine

PCr, Phosphocreatine

PRESS, Point resolved spectroscopy

QUEST, Quantitation based on quantum estimation

sl, Scyllo-inositol

SD, Standard deviation

SNR, Signal-to-noise ratio

SVS, Single voxel spectroscopy

Tau, Taurine

VESPA, Versatile simulation- pulses and analysis

VOI, Volume of interest

WS, Water-suppressed

INTRODUCTION

Magnetic resonance spectroscopy (MRS) is a non-invasive method that can provide clinically relevant metabolic information (1). Despite the evidence for the value of MRS in clinical practice and despite of technical improvements, the application of MR spectroscopy is still limited because of its challenging nature of interpretation, expert knowledge requirement (2), but also because of time constraints in the clinical setting.

Relative to MRI, MRS has much lower sensitivity and thus requires much longer acquisition times. In addition, MRS requires a more homogeneous B_0 field than MRI to achieve sufficient separation of metabolite resonances, hence necessitating dedicated shimming for each region of interest (ROI) – again prolonging overall acquisition time.

The quantification of in vivo localized proton MR spectra is affected by the signal-to-noise ratio (SNR), broadened line shapes due to inadequate shimming, presence of a non-flat baseline often related to insufficient water suppression, and inherent limits of the contributing spectral components, including overlapping peaks, and the incomplete prior-knowledge in particular with regard to the macromolecular baseline. From the experimental factors, linewidth (LW) and SNR may serve as the main physical measures to rate the quality of spectra (2). The effects of SNR and LW on metabolite concentrations have been investigated at 1.5 T and 4 T (3,4) to show that as SNR decreases or the linewidth broadens, the quantification accuracy clearly decreases. These results suggest that – within limits – knowledge of SNR and LW alone may serve to forecast the achievable quantification accuracy, if other parameters such as patient motion, scanner drift, degrading effects of water suppression, etc., do not interfere for the longer acquisition of the water-suppressed spectrum. Knowledge of the achievable quantification accuracy before actual acquisition of a water-suppressed spectrum may substantially influence the course of clinical MR examinations.

In present clinical routine, the usual protocol consists of choosing the ROI to acquire the spectrum from, optimizing acquisition settings, including shimming, followed by acquisition of the water-suppressed spectrum and - usually afterwards - acquisition of a single-shot water-unsuppressed spectrum for referencing. If expert knowledge is available at that time, a real time evaluation of spectral quality may influence the decision to acquire more repetitions to improve SNR or to change location to improve the shim. If at this point or later in off-line post-processing data quality is found to be insufficient, the scanner/patient time used (including shimming, voxel

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3 placement, and actual scanning) is wasted and often there is no time and opportunity to re-
4 record the spectrum with better-suited acquisition parameters.
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7 Particularly for focal lesions where the size and location of the ROI is different from case to
8 case, even for the expert, it is not straightforward to forecast how long signals should be
9 averaged and how well the ROI has to be shimmed in order to arrive at an interpretable
10 spectrum for the particular clinical question. The operator would have to take into account
11 factors like the size of the ROI, the quality of the shim (influenced by proximity to skull/bone/air
12 transitions, or presence of blood), the field strength and other hardware specifics. However,
13 achievable SNR and LW can essentially be known from a single water-unsuppressed
14 acquisition and if this reference data is acquired before the lengthy recording of water-
15 suppressed data, the decision to go ahead could be taken on more objective grounds. In
16 addition, using the square root dependence of SNR with regard to the number of averages (2),
17 the water signal could be used as basis to forecast how many signal averages will be needed,
18 to achieve a minimally required quantification precision.
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27 In this study, the effects of SNR and LW on metabolite concentrations at 3 T were modeled and
28 it was investigated whether this information could be used to forecast the best achievable
29 modeling inaccuracies for the metabolites of interest before the relevant water-suppressed data
30 is recorded and thus to influence the acquisition parameters for the subsequent acquisition of
31 the water-suppressed spectrum. The performance of the forecast was investigated using
32 simulated spectra and then verified for in vivo spectra of human brain for all major metabolites,
33 including myo-inositol and glutamate.
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42 **METHODS**

43 **Simulation**

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45 Brain metabolite spectra were simulated in Vespa (5) using spin Hamiltonian parameters of
46 metabolites (6,7) for ideal short and long echo time PRESS localization (echo times (TEs) 30
47 ms and 136 ms) and scaled to yield a normal brain spectrum based on concentrations and T_2
48 values from literature (8,9). Simulated metabolites for short TE included aspartate (Asp), γ -
49 aminobutyric acid (GABA), creatine (Cr), glucose (Glc), glutamate (Glu), glutamine (Gln),
50 glycine (Gly), glycerophosphocholine (GPC), glutathione (GSH), lactate (Lac), myo-inositol (ml),
51 N-acetylaspartylglutamate (NAAG), N-acetylaspartate (NAA), phosphocholine (PCho),
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3 phosphocreatine (PCr), scyllo-inositol (sl), taurine (Tau). Asp, GABA, Glc were not included for
4 long TE spectra due to their T_2 -attenuated minor contributions. Similarly, a water spectrum was
5 simulated and scaled using a T_2 for water of 80 ms (10) and an assumed water content
6 specified by the user (see below). The linewidths for the simulated base spectra of metabolites
7 and water were 2 and 4 Hz, respectively.
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13 A macromolecular baseline (MMBL) signal was also added for the simulated short TE spectra.
14 The MMBL had been acquired from 10 human subjects in a 2DJ experiment with the metabolite-
15 nulling technique (11) using an inversion time of 900 ms and TEs ranging from 20 to 95 ms. For
16 the short TE baseline spectrum, the macromolecule spectra from TE=25, 30, and 35 ms were
17 averaged to create an approximate TE=30 ms spectrum. The MMBL spectrum was
18 preprocessed to remove water and metabolite residuals using Hankel-Lanczos Singular Value
19 Decomposition (HLSVD). Then the MMBL spectrum was modeled as sum of Lorentzians by
20 HLSVD with restraints on damping constants to obtain a noiseless representation of the MMBL
21 spectrum. The linewidths of the base components of this MMBL spectrum were then adjusted to
22 match a metabolite spectrum of 2 Hz width.
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31 These in silico spectra (water and metabolites) were used to generate spectra with different LW.
32 First, the water spectrum was apodized to feature LWs ranging from 5 to 15 Hz in 1 Hz
33 increment, using different Gaussian damping factors. The same damping factors were then
34 applied to the corresponding metabolite spectra.
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39 For each LW, 100 spectra of different noise realizations were created to obtain data sets at 18
40 SNRs ranging from 5 to 300 (5, 10, 15, 20, 30, 40, 50, 60, 70, 80, 90, 100, 125, 150, 175, 200,
41 250, 300), where SNR was defined in time domain (TD) as amplitude of the first point of the
42 overall metabolite signal divided by the standard deviation of the noise in the TD signal. In total,
43 19800 spectra were created for both short and long TE.
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49 Quantification

50 Simulated spectra were quantified using the two most widely used fitting packages (LCModel
51 (12) and jMRUI (QUEST) (13)). QUEST is a pure TD method whereas LCModel is using the
52 frequency domain (FD) for least squares minimization (14).
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3 LCMoDel works fully automatic and operator-independent to decompose an in vivo spectrum
4 into a linear combination of model spectra provided as prior knowledge. It also estimates a
5 flexible lineshape model and a spline baseline that accounts for model imperfections (12,15). In
6 this study, LCMoDel was used in the standard configuration with the analyzing window from
7 0.2 to 4 ppm.
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13 QUEST also quantifies spectra by utilizing model spectra as prior knowledge. To accommodate
14 a baseline it uses a three step procedure. It is assumed that the background signals have short
15 T_2 and therefore truncating the initial points would separate the background from the metabolite
16 signals (16,17). So first, initial points are truncated and the metabolite parameters are estimated
17 on the truncated fid. The fitted truncated signal is then back-projected to the time origin and
18 subtracted from the original signal to get the noisy background signal. In the second step, the
19 noisy background signal is modeled by Lorentzian components using SVD. In the third step, the
20 parameterized background signal is either subtracted from the raw signal or – as applied here -
21 used as a further model component (option “InBase”) and a parametric nonlinear least-squares
22 fit is performed in TD. In our study, the linewidth parameter was allowed to range between -10
23 and +150 Hz while frequency shifts were not allowed, assuming previous overall alignment and
24 no relative shifts of metabolite components. The ‘InBase’ option was chosen with 5 truncation
25 points, which was found optimal to model very broad baseline components for the case where
26 the MMBL are handled by including a MMBL spectrum in the basis set. .
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37 Both methods yield estimates for metabolite content along with Cramer-Rao lower bounds
38 (CRLB) for the fitting errors. CRLB (18) reflect minimal uncertainties for each fit as given by the
39 interdependence of fitting parameters in the model and the experimental noise level associated
40 with the measurement. The CRLB represent the lowest possible error, with overall uncertainties
41 bound to be larger because of additional experimental uncertainties.
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47 Prior knowledge for the quantification included the information describing all resonances present
48 in the simulated spectra. For short TE spectra, the MMBL spectrum was also included as basis
49 spectrum since it has been shown (19) that inclusion of a metabolite-nulled spectrum in the
50 basis set leads to more reliable and accurate metabolite quantification than using the estimated
51 MMBL from LCMoDel. For QUEST, at both long and short TE, the prior knowledge did not
52 include separate Cr and PCr but rather a sum of Cr and PCr (50:50), in order to obtain an
53 estimate and CRLB of total creatine ($Cr_{tot} = Cr + PCr$).
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The median CRLB, median bias (fit minus true values) and the standard deviations (SD) of metabolite contents across 100 spectra were calculated for each combination of LW and SNR and tabulated for the forecasting tool. The medians were preferred over averages for their insensitivity to single cases where the fit algorithm may not have found the global χ^2 minimum.

The absolute concentrations and CRLB error estimates were calculated with respect to water. LCMoDel provides the CRLB in percent, so to express them in absolute values; they were multiplied with the estimated concentrations.

Forecast tool

For forecasting metabolite errors in the form of CRLB of fitted spectra for metabolite content based on the water spectrum, first the linewidth of the experimental non-water suppressed spectrum was determined by fitting the signal to a Voigt lineshape. Then the expected SNR of the metabolite spectrum was calculated based on the proposed number of averages, the TE and the water content (WC) of the ROI as indirectly indicated by the user as relative white and gray matter content of the ROI. 75% water content in pure gray matter and 65% in pure white matter were assumed. (T_1 -relaxation effects and CSF contributions to the water signal are currently neglected in this prototype tool).

Equation 1 shows how the expected TD SNR of the metabolite spectrum was calculated based on a single acquisition of the water signal.

$$\text{Expected SNR of metabolite TD signal} = \left(\frac{SNR_{water}}{K} \right) \sqrt{\text{averages} / WC} \quad [1]$$

where

SNR_{water} is the SNR in the single shot water signal,

$$K = \frac{\text{initial magnitude of TD signal of simulated water}}{\text{initial magnitude of TD signal of sum of simulated metabolite signals}}$$

and averages stands for the prescribed number of acquisitions for the water-suppressed spectrum.

Using LW and the SNR information, the errors associated with each metabolite concentration estimate were determined by interpolation of the tabulated values.

The whole procedure of forecasting is shown in a flowchart in Figure 1

Performance testing

In-silico

To test how well the forecast works at best, the water spectra simulated with varying LWs and SNRs were treated as experimental spectra to forecast the metabolite errors for the associated metabolite spectra. The differences with respect to CRLB as well as the true variance found in the model fits were investigated as a function of LW and SNR for both short and long TE.

In-vivo

The forecast tool was then applied to in-vivo cases. Twelve healthy subjects (4 women and 8 men) gave informed consent according to the procedure approved by the local ethics committee. The scans were performed on 3-T scanners (Trio and Verio, Syngo MR VB17 Siemens, Erlangen, Germany) using 16 channel phased array receive-only head coils. Each measurement session included basic MRI to define the ROIs for MRS. First- and second-order shims were adjusted using FASTESTMAP (20). Water suppressed, as well as unsuppressed spectra were acquired using a standard PRESS sequence at TE = 30 ms and 136 ms, TR = 3000 ms, number of acquisitions ranging from 16 to 128, ROI size ranging from 1.6 to 9.1 cm³ (with typical dimensions from 16x10x10 mm³ to 40x19x12 mm³) and from different parts of the brain (frontal, occipital, supraventricular) containing both white matter and gray matter.

The in vivo spectra were analyzed using jMRUI and LCModel with parameters set as described for the simulated datasets. For jMRUI, preprocessing included eddy current-correction using the phase information of the water spectrum and removal of residual water using HLSVD decomposition. In LCModel, the option to do eddy-current-correction using the phase information of the water reference was chosen. Residual water was not removed.

RESULTS

Forecasting with LCModel

LCModel was able to quantify all 19800 simulated metabolite spectra at short and long TE. Figure 2 shows representative spectra and fit results from the large set of simulated spectra,

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3 illustrating that LCModel (left panel) did not yield substantial systematic residuals in any of the
4 situations, i.e. neither for a spectrum with substantial noise (SNR 20) in row a, nor the noiseless
5 cases without broadening (row b) or with 10 Hz Gaussian broadening (row c), where LCModel
6 profits from a flexible shape estimation with sufficient freedom to adapt to Gaussian broadening.
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10 Systematic residuals would lead to bias for the estimated metabolite contents. The median bias
11 expressed as percentage of the true concentrations was found to be very small or even
12 negligible for LCModel at short TE with +3%, +2%, +3%, +4%, -3% and <1% for Cr_{tot} , NAA_{tot} ,
13 Glu, Glx, mI_{tot} and Cho_{tot} , respectively. Similar results were found at long TE.
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17 Figure 3 and Figure 4 illustrate the database used for developing the forecast tool with esti-
18 mated CRLB and true variance found when fitting the simulated spectra. The true variance i.e.
19 the SDs of metabolite estimates across the 100 spectra for each particular combination of LW
20 and SNR was compared to the CRLB given by the fitting tool. These figures show the average
21 CRLB (on the left) and true variance in estimated metabolite content (on the right) as a function
22 of LW and SNR for a selection of metabolites in the cases of short (LCModel results in Fig 3a)
23 and long (Fig 4a) TE. As expected, uncertainties of estimated metabolite contents, reflected in
24 CRLB and true variance, generally increase when the lines broaden or SNR decreases. CRLB
25 and true variance show similar values and dependences for LCModel. In general, it was found
26 that the CRLB somewhat overestimate the variance of fitting results. In particular at TE 30 ms,
27 the ratio between CRLB and true SD was between 1.05 and 1.29 for the major metabolites.
28 Looking into the detailed dependence of the comparison between CRLB and true variance on
29 linewidth, we find that e.g. for Cr_{tot} , the ratio increased from 1.1 at FWHM of 5 Hz to 1.3 at
30 15 Hz.
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41 These sets of CRLB and true variance were then translated into large lookup tables for
42 expected errors based on estimated SNR and LW of the related single shot water signals. Figs
43 3 and 4 represent these look-up tables. To judge the in silico performance, the mean absolute
44 difference between the forecast error based on the water signal and the actual error found from
45 the fits was evaluated. At short TE, the maximum difference was just 1% for LCModel, such that
46 from the synthetic data it appears that an error forecast based on the water signal seems
47 feasible for many metabolites.
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53 The proposed scheme was verified on in vivo spectra that had SNR and FWHM ranging from 5
54 to 190 and 5 to 14 Hz, respectively. Example in vivo data is shown in Figure 5 with different
55 LWs, SNRs, voxel location and TEs. The top row shows the initially acquired water scan with
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3 estimated linewidth and SNR. The middle row presents the predicted CRLB values from the
4 look up table and simulated water-suppressed spectra that closely match the corresponding LW
5 and SNR. The bottom row illustrates the subsequently actually acquired in vivo metabolite
6 spectra and the CRLB values obtained for their fits. Figures 6 to 7 document the outcome for all
7 in vivo cases by presenting the correlation between the predicted CRLB based on the water
8 acquisition and those found from the fitting results of the actually recorded WS spectra for some
9 metabolites. In addition, a Bland-Altman plot is added for each correlation to investigate
10 potential systematic deviations. Results are illustrated for short (Figure 6) and long (Figure 7)
11 TE. The coefficients range between 0.73 and 0.91 for the metabolites shown. The Bland-Altman
12 plots show a very small but significant offset for some of the metabolites and no significant bias
13 for others. The confidence intervals for the deviation between forecast and actual errors as
14 given in the plots range between ± 0.03 mM (Ch_{tot}) and ± 0.3 mM (Glu and Glx) for the case of
15 short TE in LCModel. The situation is similar at long TE.
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27 ***Forecasting with jmrui/QUEST***

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29 The major outcome was similar when using QUEST instead of LCModel, but the fact that
30 QUEST is restricted to Lorentz-broadening lead to larger systematic deviations and a weaker
31 performance for the CRLB forecasts. The major differences to LCModel are presented in detail
32 in the following.
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37 QUEST was able to quantify all long TE spectra, but failed for 2.6% of the short TE cases. Fit
38 results for jMRUI's QUEST (Figure 2 right panel) are similar to those of LCModel in cases with
39 substantial noise (row a), and also for the noiseless case without broadening (row 2b).
40 However, residuals are much larger for QUEST for a case with 10 Hz Gaussian broadening
41 (row 2c), where the Voigt lines are dominated by the Gaussian broadening but are fitted with a
42 purely Lorentzian lineshape model.
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47 These systematic residuals are reflected in substantial bias for the estimated metabolite
48 contents in the synthetic spectra for some of the investigated cases. The median bias at short
49 TE was found to be much larger for QUEST than for LCModel with values of +32% and +29%
50 for Cr_{tot} and Glu compared to +3% for both cases when using LCModel.
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54 For QUEST, the comparison between average CRLB (on the left in Figs 3 and 4) and true
55 variance (on the right in Figs 3 and 4) as a function of LW and SNR is hampered by the fact that
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QUEST does not provide CRLB estimates for sums of metabolites, but - where available - the differences between true variance and estimated CRLB are larger for QUEST than for LCModel. As with LCModel, it was found that the CRLB overestimate the variance of fitting results systematically. However for QUEST, even though the noise was calculated using the original data and not the residues, the ratio between CRLB and true SD was larger and in the range of 2.1 to 3 compared to below 1.3 for LCModel.

Looking at the in silico performance, the mean absolute difference between the forecast error and the actual error was found to be somewhat larger for QUEST than LCModel (maximum difference of 8 vs. 1%), but still small enough to promise valid results also for QUEST.

Results for the in-vivo performance of error forecasts using QUEST are illustrated for short TE (Figure 8) and long TE (Figure 9). For QUEST, correlation coefficients range between 0.78 and 0.89, similar to the values for LCModel while Bland-Altman plots similarly show small but significant offsets for some metabolites. The confidence intervals for these deviations (see Figs 8-9) are again somewhat larger for QUEST.

DISCUSSION

A water-unsuppressed signal is nearly always recorded in clinical MRS investigations and can be used as a reference for lineshape correction and as an internal reference for absolute metabolite quantitation. Here, we show that it is also possible to use such a single-shot water signal to forecast an estimate for the quantification error that will be associated with the fitting result for most relevant metabolites from the subsequently recorded water-suppressed spectrum. The forecast is based on the linewidth and SNR of the water data, as well as the planned number of acquisitions.

Clinical MRS exams are most often performed by non-expert personnel. They cannot judge the quality of the acquired water scan or spectrum and thus whether or not any targeted question about potential changes in metabolite content could possibly be answered given the foreseen or even the already acquired spectrum. The possibility to forecast fitting errors would allow defining minimal quality prerequisites to be fulfilled for an MR spectrum to be recorded under the planned acquisition settings. In particular, this may allow the non-specialist (and even the experienced user) to better judge in real time, i.e. with the patient still in the scanner, how many acquisitions should be prescribed for a certain clinical question, or whether under the given

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3 circumstances the ROI should be increased or possibly moved away from areas of potential
4 susceptibility problems to obtain narrower linewidths. If quality screening is only performed after
5 acquisition of the WS spectrum, time will often not allow for improved or prolonged spectral
6 acquisitions and of course if spectral processing is done off-line, enhanced or longer
7 acquisitions are not feasible.
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12 Not very surprisingly, the forecast worked very well for the synthetic cases, also when
13 comparing the observed variance from fitting 100 different spectra per case with the forecast
14 CRLB. But as evident from Figs. 6 to 9, the error forecast showed very good accuracy also in
15 vivo. For reasons of limited space, the results were only presented for the clinically most
16 interesting metabolites (and for this reason primarily for the more accurately defined sums of
17 metabolites with a similar spectrum) at both echo times, but results are similar for the other
18 metabolites and there is no reason why it could not be used for any metabolite or other
19 acquisition condition, if needed.
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26 However, the value of the forecast is limited in several aspects. 1) The forecast errors provide a
27 best case scenario. If the patient moves, or acquisition conditions are not constant for other
28 reasons, the forecast may be incorrect. Also, if the WS spectrum should be plagued by artifacts
29 (2), the best case scenario would not apply – thus the proposed tool should only be seen as a
30 minimal quality requirement, not as a guarantee for eventual success of the MRS exam. In fact,
31 it should be seen as a warning system for likely failure, not as an indicator of probable success.
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33 2) The proposed forecast tool should be implemented in a real time version, best on the scanner
34 console or at least with automatic transfer and evaluation on a satellite station next to the
35 scanner, since otherwise the time benefit would be wasted. 3) For each clinical question a
36 threshold uncertainty has to be predefined requiring the experience of previous investigations,
37 but this can be defined based on literature data. 4) The currently presented forecast is based on
38 spectra that are composed of those metabolites that occur in healthy brain. Interference with
39 other spectral elements, e.g. lipid resonances, may be investigated in addition.
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48 Further limitations concern general issues of fitting MR spectra, where it is known that results
49 will depend on the fitting and processing routines used and in particular the prior knowledge
50 constraints included. Hence the forecast errors will only be applicable if an evaluation similar to
51 the one used to define the forecast tool is being used. This has become evident from the
52 comparison of the LCModel and QUEST results, as described above. In particular, baseline and
53 lineshape issues may well modify the results and the effective fitting error drastically. The
54 baseline signals pose a challenge for obtaining reliable estimates, because they may have
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3 unknown shapes and intensities and may include lipids. The macromolecules and lipids also
4 vary based on pathologies (21–25). Accurate estimation of macromolecules is needed for
5 reliable quantification of metabolites. For the synthetic spectra used in this study, this was
6 confirmed when comparing different evaluation schemes for both LCModel and QUEST, when
7 we did or didn't use a macromolecular baseline as part of the basis set (results not shown). For
8 QUEST, the results depended heavily on the algorithm of baseline incorporation (e.g. number of
9 initial data points to use for baseline definition). In particular, the baseline is a serious problem
10 when the spectral resolution is low. Over- or underestimation of the macromolecule signal may
11 strongly influence content and CRLB of the overlapping metabolites with broad spectral
12 patterns. It should also be noted that the forecast errors as defined in the present set up would
13 not be correct in cases of pathology, when other base spectra would be introduced, or lipids
14 would have to be included in the fit.
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23 The lineshape due to the remaining field inhomogeneity after shimming is often non-Lorentzian
24 and thus fitting with pure Lorentzians easily leads to systematic errors (26). Experimental
25 lineshapes are more precisely modeled by a Voigt function (multiplication of Lorentzian and
26 Gaussian damping). Hence, we used the Voigt lineshape to fit the water spectrum for the
27 determination of the water linewidth. If the true LWs deviate from this model, this might impact
28 on the forecast. This is currently not considered, but a check of lineshape could be included in
29 the forecast. The fact that QUEST in its current form did not allow for use of Voigt lines or
30 general lineshapes certainly is the reason why it showed considerable bias. In contrast,
31 LCModel uses a regularized lineshape model that accounts for the unknown lineshapes thus
32 reducing effects of lineshape on bias. The effect of the used lineshape is evident in Fig. 2.
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40 A minor issue that has not been treated in depth so far is the exact water content of the
41 investigated ROI. At present, this is included indirectly with the user describing the ROI content
42 in terms of white/grey matter percentage. Using a proton density map – possibly augmented
43 with automatic tissue segmentation, this could be circumvented, such that also for cases of
44 cysts and necrosis proper scaling could be achieved (27).
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49 The fitting results from the vast set of simulated spectra with differing SNR and LW also yielded
50 insight into the performance of LCModel and QUEST as well as into general dependence of fit
51 results on LW and SNR. Figs 3 -4 illustrate this dependence with the diagrams on true variance
52 (right side panels). The outcome is similar to earlier investigations (3,4). It should be noted that
53 these diagrams depend strongly on whether the SNR is defined in time or frequency domain.
54 Here we have used the TD definition, because in this way SNR does not depend on the
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3 linewidth. With the FD definition of SNR, constant SNR with variable linewidth implicate differing
4 acquisition times. Thus, in the presented figures, one can observe the expected larger variance
5 for an increase in linewidth whereas if the SNR is defined in frequency domain, one may even
6 detect a decrease in the measurement error with increased linewidth just because this mixes
7 the effect of linewidth and length of acquisition time.
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11 From Figs 3 and 4, it seems that the absolute error for long TE is generally lower than for short
12 TE. This is only true for identical SNR, but to achieve similar SNR in these particular cases, it
13 would roughly take at least twice as long at the longer TE. Hence, for equal acquisition times,
14 the fitting errors for those compounds that can be measured at both echo times would probably
15 be about the same.
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19 As an outlook, the performance of this forecast tool might be optimized by use of actual in vivo
20 data as part of the look-up table, where one might also improve the performance by including
21 lineshape characteristics other than the simple LW and possibly machine learning algorithms for
22 the predictor.
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26 In conclusion, our results indicate that it is possible to forecast the errors associated with
27 specific metabolites to be found in model fits of WS spectra based on a single shot water signal.
28 Thus, the clinical MRS user will be able to judge ahead of time whether the planned acquisition
29 can possibly be of sufficient quality to answer the question at hand or whether it needs more
30 averages or improved shimming.
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40 **Acknowledgement**

41 This research was carried out in the framework of the European Marie-Curie Initial Training
42 Network, 'TRANSACT', PITN-GA-2012-316679, 2013-2017 and also supported by the Swiss
43 National Science Foundation (#320030_156952).
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15 resonance spectroscopy and tissue characterization of human brain tissue based on the use of
16 quantitative magnetic resonance imaging. *Magn Reson Med.* 2013;70:905–915.
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Figure Captions

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25 **Figure 1:** Flowchart illustrating the forecasting procedure. The steps marked in blue are
26 calculated by the toolbox while the steps marked in pink represent input by the user.
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32 **Figure 2:** Illustration of the fits in LCMoDel and QUEST for simulated PRESS ¹H-MR spectra at
33 TE=30 ms. a) FWHM = 7 Hz, SNR = 20; b) FWHM = 2 Hz (Lorentzian lineshape), no noise
34 added; c) FWHM = 10 Hz (Voigt lineshape), no noise added. The residuals (original spectrum
35 minus fit) are shown above the spectra. For QUEST, the original spectra and their
36 corresponding fits were zero-filled before plotting for better comparison, since zero-filling is part
37 of the LCMoDel data treatment.
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45 **Figure 3:** Mean variance for some estimated metabolite content obtained for simulated spectra
46 at short TE when fit with LCMoDel (a) and QUEST (b). For both cases, the mean CRLB is
47 shown on the left and standard deviations of the determined metabolite contents as obtained
48 over 100 different noise realizations on the right.
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51 Since QUEST does not provide error estimates of summed metabolite areas, some diagrams
52 are missing. It should also be noted, that for $C_{r_{tot}}$ (where we do indicate CRLB values even in
53 the case of QUEST), we had included a base spectrum for a 50/50 mixture of Cr and PCr,
54 rather than individual spectra in the case of QUEST.
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3 *Abbreviations:* Cho_{tot} = Glycerophosphocholine + Phosphocholine; Cr = Creatine; CRLB =
4 Cramer-Rao-lower bound; Cr_{tot} = Creatine + Phosphocreatine; Glx = Glutamate + Glutamine;
5 ml_{tot} = myo-Inositol + Glycine; NAA_{tot} = N-acetylaspartate + N-acetylaspartyl-glutamate; PCr =
6 Phosphocreatine; TrueSD= true standard deviation.
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12 **Figure 4:** Mean variance for some estimated metabolite content obtained for simulated spectra
13 at long TE when fit with LCModel (a) and QUEST (b). For both cases, the mean CRLB is shown
14 on the left and standard deviations of the determined metabolite contents as obtained over 100
15 different noise realizations on the right.
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19 Since QUEST does not provide error estimates of summed metabolite areas, some diagrams
20 are missing. It should also be noted, that for Cr_{tot} (where we do indicate CRLB values even in
21 the case of QUEST), we had included a base spectrum for a 50/50 mixture of Cr and PCr,
22 rather than individual spectra in the case of QUEST. For Abbreviations, see Fig. 2.
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29 **Figure 5:** Illustration of sample in vivo data with different LWs, SNRs, voxel location and TEs.
30 The top row shows the single shot water scan. The water line width is calculated, and based on
31 the TE and voxel composition, the SNR is estimated. The middle row shows simulated water
32 suppressed spectra representing the estimated SNR and LW as well as the predicted CRLB
33 from the look-up table. Note that the simulated spectrum is just for illustration and that the SNR
34 and LW do not match exactly. The bottom row shows the subsequently acquired in vivo
35 metabolite spectra and the corresponding CRLB obtained from fitting these spectra.
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44 **Figure 6:** Illustration of the in vivo performance of the proposed error forecast method for the
45 case of LCModel at short TE. The graphs on the left show the correlation between the forecast
46 error using the single water shot and the CRLB as determined from fitting the corresponding
47 water-suppressed spectra, while on the right the same data is presented in the form of Bland-
48 Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots
49 include 95 % confidence intervals for the differences and the significance values for these
50 offsets.
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Figure 7: Illustration of the in vivo performance of the proposed error forecast method for the case of LCMoDel at long TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

Figure 8: Illustration of the in vivo performance of the proposed error forecast method for the case of QUEST at short TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

Figure 9: Illustration of the in vivo performance of the proposed error forecast method for the case of QUEST at long TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

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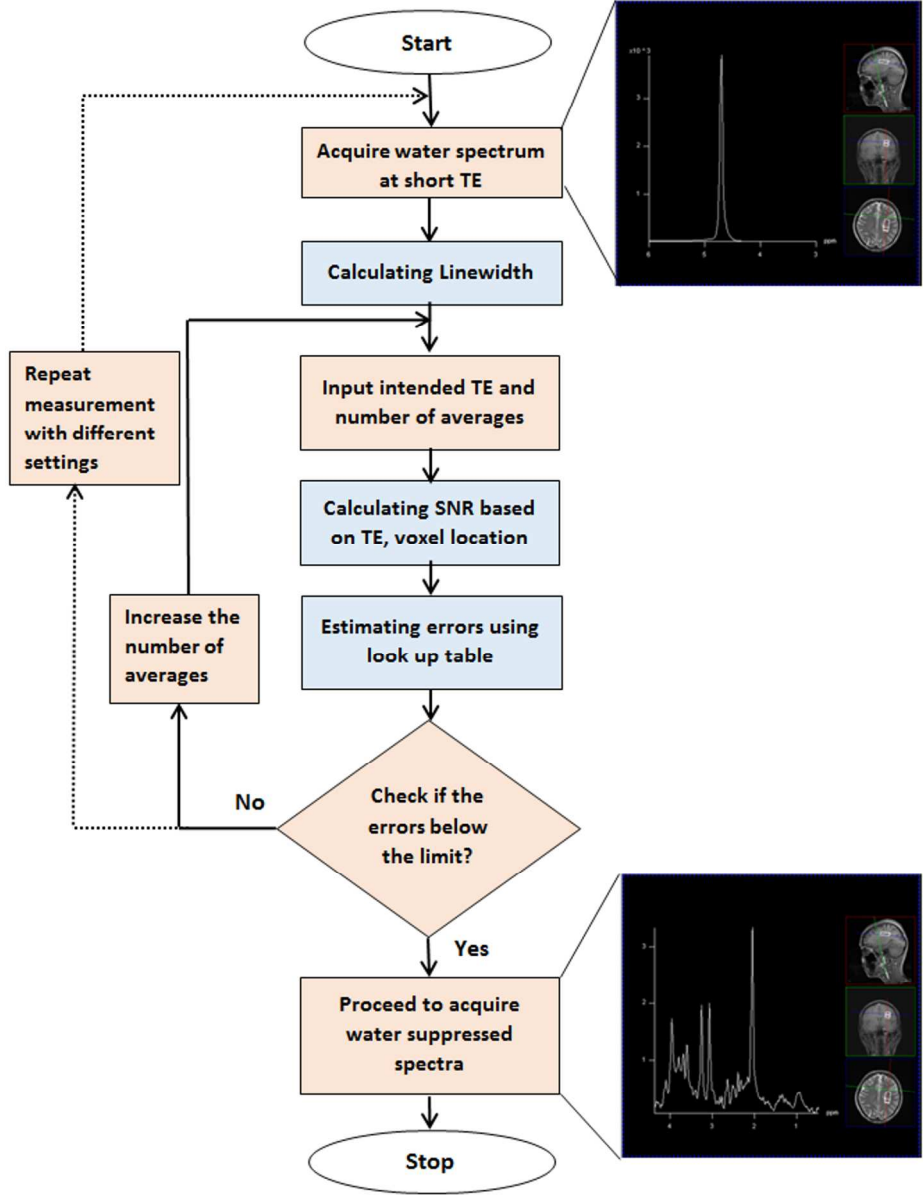


Figure 1: Flowchart illustrating the forecasting procedure. The steps marked in blue are calculated by the toolbox while the steps marked in pink represent input by the user.

Figure 1
229x299mm (300 x 300 DPI)

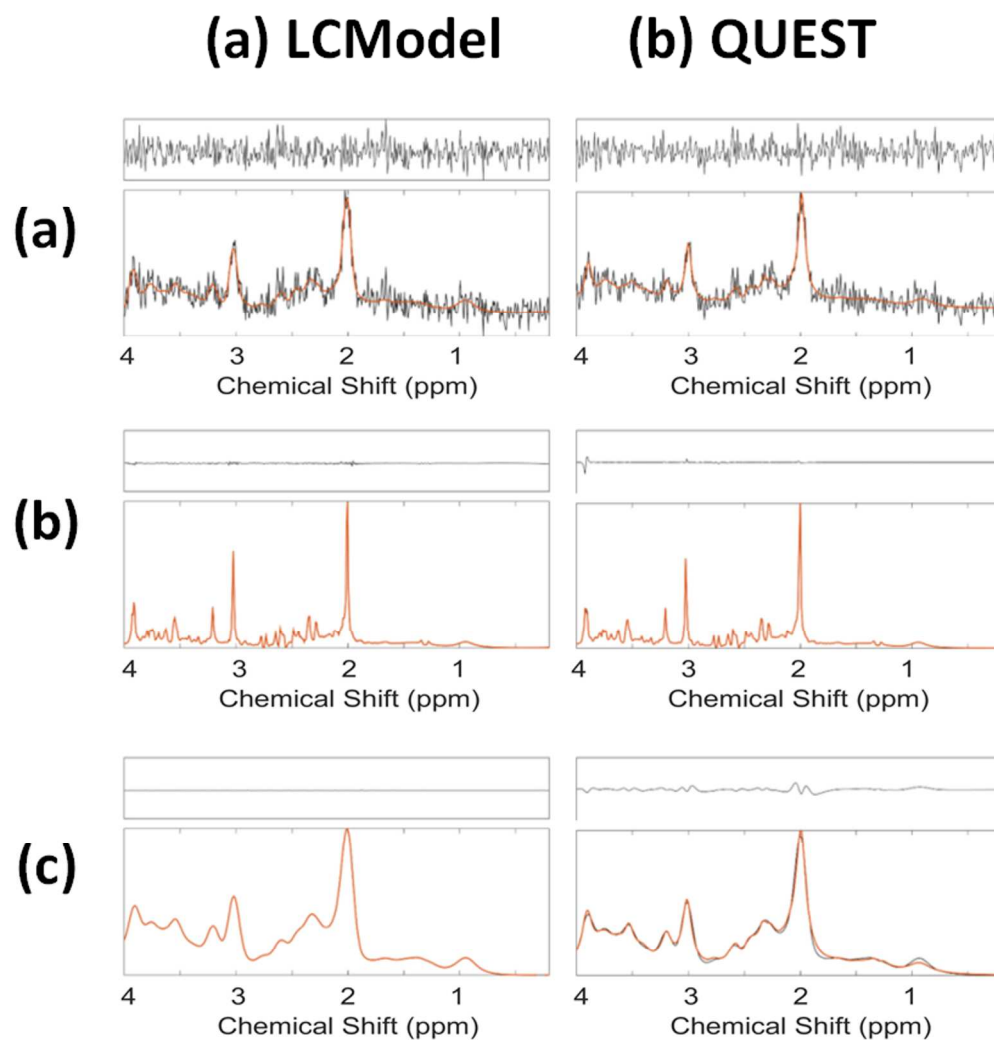


Figure 2: Illustration of the fits in LCMoDel and QUEST for simulated PRESS 1H-MR spectra at TE=30 ms. a) FWHM = 7 Hz, SNR = 20; b) FWHM = 2 Hz (Lorentzian lineshape), no noise added; c) FWHM = 10 Hz (Voigt lineshape), no noise added. The residuals (original spectrum minus fit) are shown above the spectra. For QUEST, the original spectra and their corresponding fits were zero-filled before plotting for better comparison, since zero-filling is part of the LCMoDel data treatment.

Figure 2

91x96mm (600 x 600 DPI)

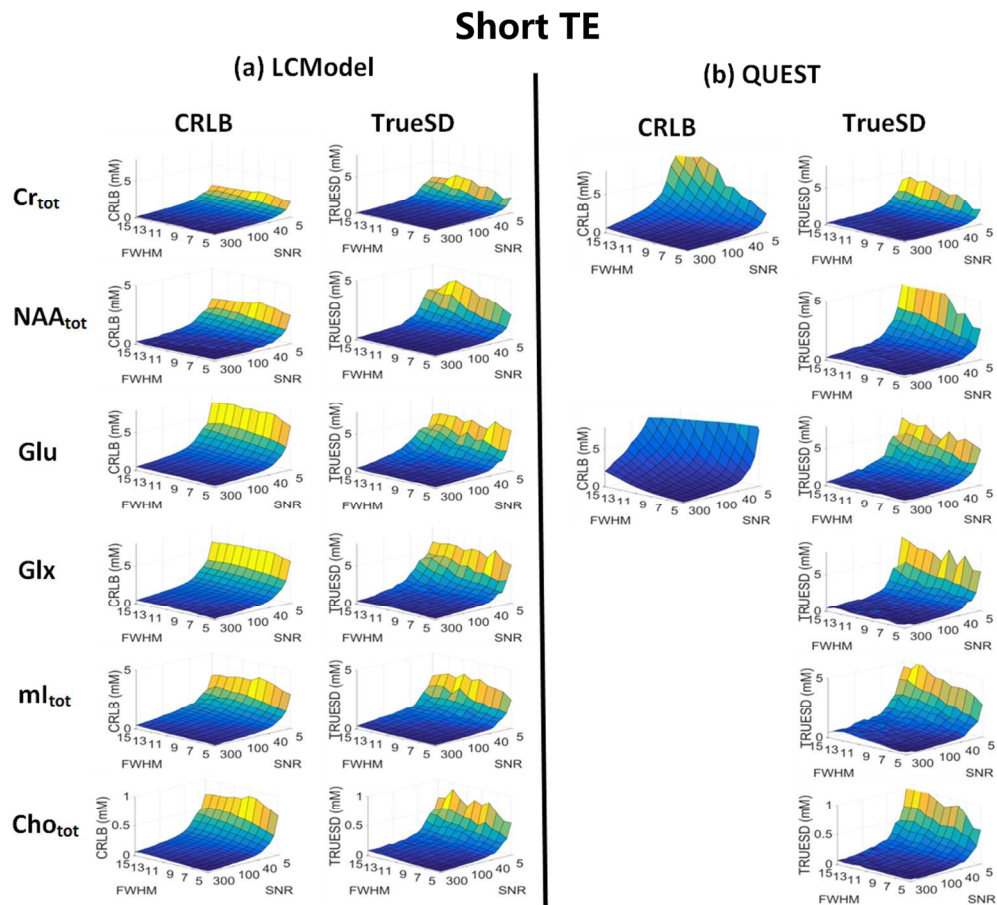


Figure 3: Mean variance for some estimated metabolite content obtained for simulated spectra at short TE when fit with LCMoDel (a) and QUEST (b). For both cases, the mean CRLB is shown on the left and standard deviations of the determined metabolite contents as obtained over 100 different noise realizations on the right. Since QUEST does not provide error estimates of summed metabolite areas, some diagrams are missing. It should also be noted, that for Cr_{tot} (where we do indicate CRLB values even in the case of QUEST), we had included a base spectrum for a 50/50 mixture of Cr and PCr, rather than individual spectra in the case of QUEST. Abbreviations: Cho_{tot} = Glycerophosphocholine + Phosphocholine; Cr = Creatine; CRLB = Cramer-Rao-lower bound; Cr_{tot} = Creatine + Phosphocreatine; Glx = Glutamate + Glutamine; mI_{tot} = myo-Inositol + Glycine; NAA_{tot} = N-acetylaspartate + N-acetylaspartyl-glutamate; PCr = Phosphocreatine; TrueSD= true standard deviation.

Figure 3
160x145mm (300 x 300 DPI)

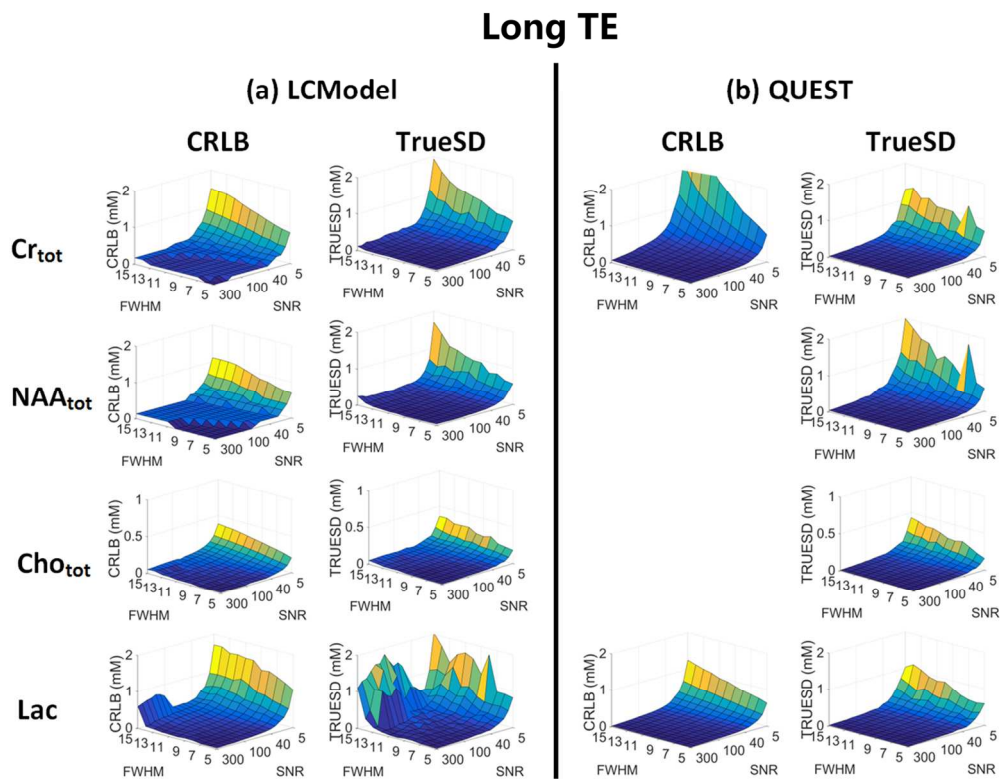


Figure 4: Mean variance for some estimated metabolite content obtained for simulated spectra at long TE when fit with LCModel (a) and QUEST (b). For both cases, the mean CRLB is shown on the left and standard deviations of the determined metabolite contents as obtained over 100 different noise realizations on the right. Since QUEST does not provide error estimates of summed metabolite areas, some diagrams are missing. It should also be noted, that for Cr_{tot} (where we do indicate CRLB values even in the case of QUEST), we had included a base spectrum for a 50/50 mixture of Cr and PCr, rather than individual spectra in the case of QUEST. For Abbreviations, see Fig. 2.

Figure 4
139x111mm (300 x 300 DPI)



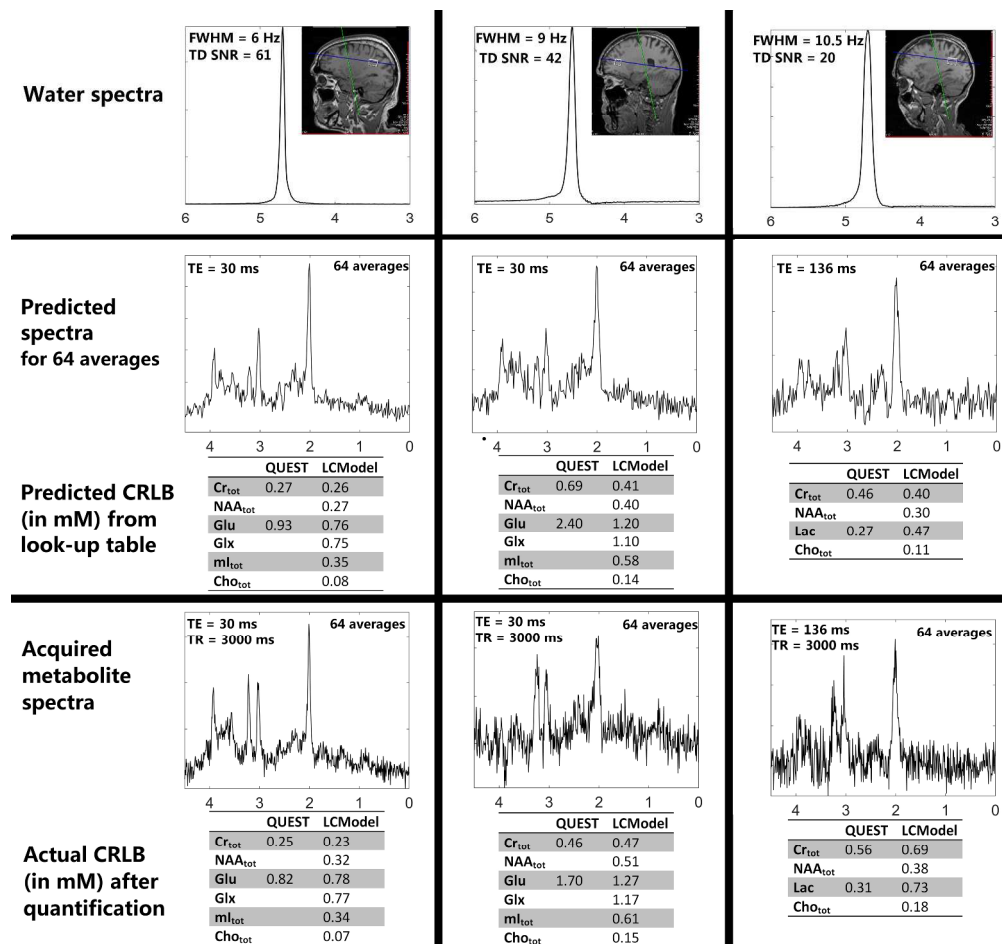


Figure 5: Illustration of sample in vivo data with different LWs, SNRs, voxel location and TEs. The top row shows the single shot water scan. The water line width is calculated, and based on the TE and voxel composition, the SNR is estimated. The middle row shows simulated water suppressed spectra representing the estimated SNR and LW as well as the predicted CRLB from the look-up table. Note that the simulated spectrum is just for illustration and that the SNR and LW do not match exactly. The bottom row shows the subsequently acquired in vivo metabolite spectra and the corresponding CRLB obtained from fitting these spectra.

Figure 5

164x154mm (600 x 600 DPI)

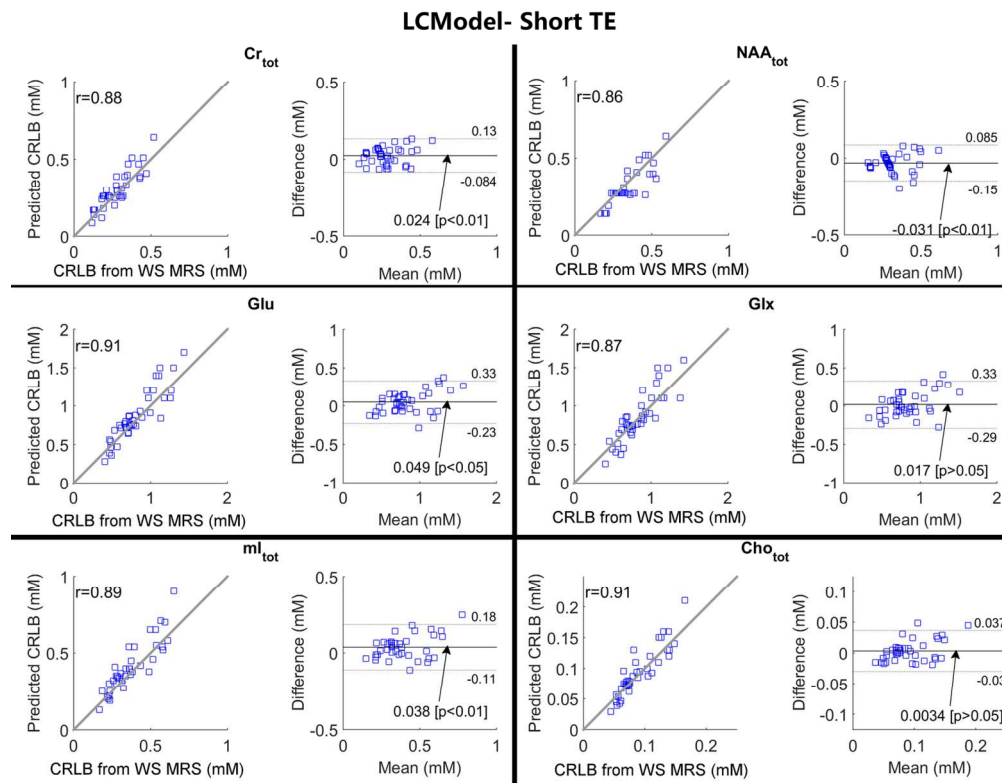


Figure 6: Illustration of the in vivo performance of the proposed error forecast method for the case of LCMoel at short TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

Figure 6
140x112mm (300 x 300 DPI)

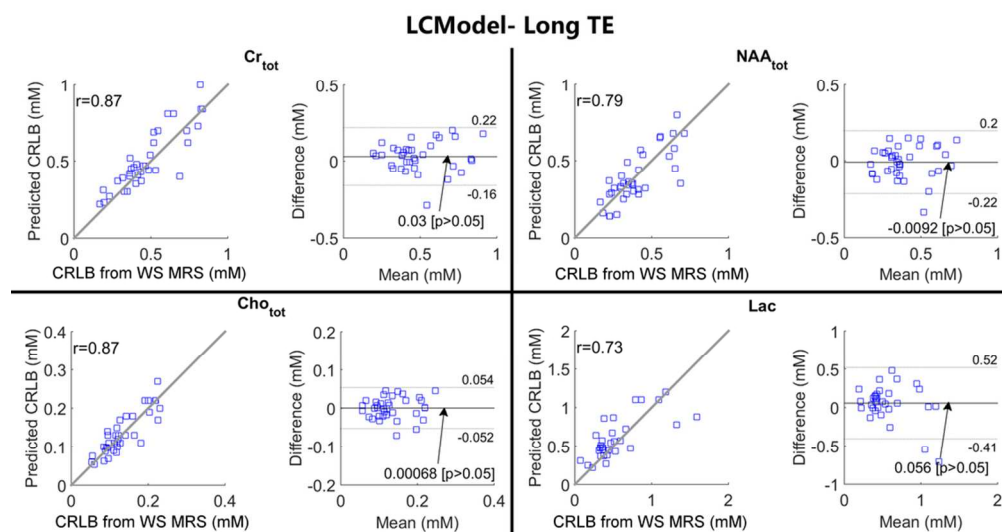


Figure 7: Illustration of the in vivo performance of the proposed error forecast method for the case of LCMoel at long TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

Figure 7

96x52mm (300 x 300 DPI)

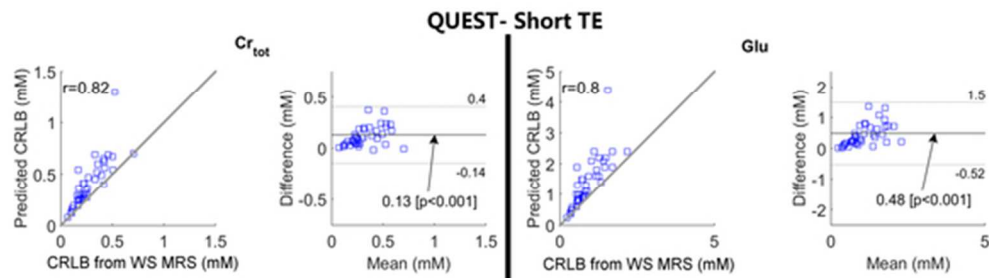


Figure 8: Illustration of the in vivo performance of the proposed error forecast method for the case of QUEST at short TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

Figure 8
49x14mm (300 x 300 DPI)

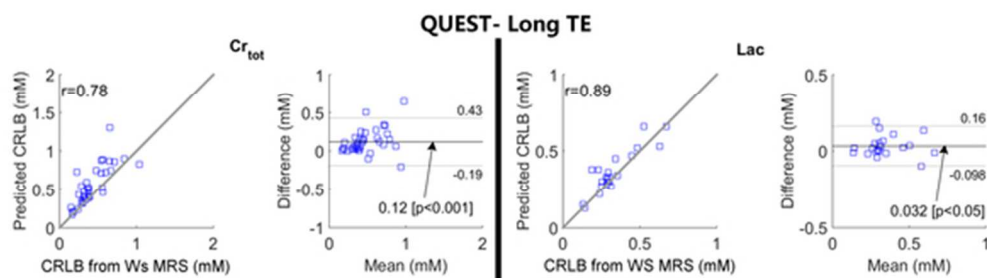


Figure 9: Illustration of the in vivo performance of the proposed error forecast method for the case of QUEST at long TE. The graphs on the left show the correlation between the forecast error using the single water shot and the CRLB as determined from fitting the corresponding water-suppressed spectra, while on the right the same data is presented in the form of Bland-Altman plots. The gray line on the correlation plot is the identity line. The Bland-Altman plots include 95 % confidence intervals for the differences and the significance values for these offsets.

Figure 9

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