

# Lin, Heydayat, Wu

## Inter Intra, and Total CCC

Comparing this paper with Barnhart, Song & Haber (SIM 2005)

	This paper	Barnhart et al
Model	$Y_{ijl} = \mu + \alpha_i + \beta_j + \gamma_{ij} + e_{ijl}$	$Y_{ijl} = \mu_{ij} + e_{ijl}$
Assump- tions	Same interaction and error variances for all observers.  Equal correlations for all pairs of observers  Independence of all random effects	Independence of means and errors
		Under ANOVA model
Intra MSD	$E(Y_{ijl} - Y_{ijl'})^2$	$E(Y_{ijl} - Y_{ijl'})^2$
Intra CCC	$(\sigma_\alpha^2 + \sigma_\gamma^2) / (\sigma_\alpha^2 + \sigma_\gamma^2 + \sigma_e^2)$	$\delta_j^2 / (\delta_j^2 + \sigma_{ej}^2) *$
Inter MSD	$E(Y_{ij\bullet} - Y_{ij'\bullet})^2$	$E(\mu_{ij} - \mu_{ij'})^2$
Inter CCC	$\sigma_\alpha^2 / (\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\gamma^2 + \sigma_e^2 / m)$	$\sigma_\alpha^2 / (\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\gamma^2)$
Total MSD	$E(Y_{ijl} - Y_{ij'l'})^2$	$E(Y_{ijl} - Y_{ij'l'})^2$
Total CCC	$\sigma_\alpha^2 / (\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\gamma^2 + \sigma_e^2)$	$\sigma_\alpha^2 / (\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\gamma^2 + \sigma_e^2)$

\*  $\delta_j^2$  is the between-subjects variability for observer  $j$ .

$$\sigma_j^2 = \delta_j^2 + \sigma_{ej}^2$$

In BSH, each observer has its own intra-CCC

Should inter-CCC be based on the observed 'within' means or on the true means?

Should it depend on  $\sigma_e^2$ ?

Should it depend on the number of replications

Other issues

Can we indeed get replicated observations?

Matched vs. unmatched replications

Agreement by chance = independence?

## Example

Three methods for assessing carotid stenosis:  
angiogram (IA), 2D-MRA, 3D-MRA. The same  
three raters measured each patient using each of the  
three methods.

<b>Inter CCC</b>	LHW	BSH	LHW	BSH
	Left	Left	Right	Right
Overall	0.668	0.763	0.742	0.848
IA vs 2D	0.675	0.755	0.761	0.846
IA vs 3D	0.556	0.624	0.689	0.765
2D vs 3D	0.773	0.925	0.778	0.943
<b>Intra CCC</b>				
Overall	0.702		0.691	
IA		0.882		0.915
2D		0.621		0.604
3D		0.614		0.616

# Barnhart, Kosinski, Haber

## ICC and CIA

$$CCC = 1 - \frac{E(Y_{i1} - Y_{i2})^2}{E\{(Y_{i1} - Y_{i2})^2 \mid \text{chance agreement}\}}$$

Does ‘chance agreement = independence’?

- Independence and (lack of) agreement are different things
- Observers are independent only if the measurements of at least one of them is independent of the true value
- So, what is ‘agreement by chance’?

CIA is based on comparing the disagreement  $MSD(Y_1, Y_2) = E(Y_{i1} - Y_{i2})^2$  to its expected value under ‘disagreement by chance’, i.e. when observers are equivalent, or interchangeable. It can be estimated from  $MSD(Y_{jk}, Y_{jk'})$  based on replicated readings by observer  $j$ .

When observer 1 is the reference, use  $MSD(Y_{1k}, Y_{1k'})$ .

When there is no reference, use the mean of  $MSD(Y_{jk}, Y_{jk'})$  over all observers.

No modification of CCC when comparing to a reference

Comparison between CCC and  $CIA^N$  in terms of the ratio of the

between-subjects and within-observers variabilities:  $d = \frac{\sigma_B^2}{\sigma_W^2}$

$$CCC = \frac{\rho_\mu}{\frac{1}{2}(\mu_1 - \mu_2)^2 + \frac{1}{d} + 1}$$

$$CIA^N = \frac{1}{\frac{1}{2}(\mu_1 - \mu_2)^2 + (1 - \rho_\mu) \cdot d + 1}$$

Both increase with  $\rho_\mu$  and decrease with  $(\mu_1 - \mu_2)^2$

CCC increases when the between-subjects variability is higher

CIA increases when within subjects  $\times$  observers variability is higher, i.e. it is more difficult to obtain a precise reading.

# Biswas

## Diagnostic Agreement

Imperfect reference test = R

New test = T

Observed two by two table:

	<b>R+</b>	<b>R-</b>	
<b>T+</b>	a	b	a+b
<b>T-</b>	c	d	c+d
	a+c	b+d	

PPA = Positive proportion of agreement =  $a/(a+c)$

NPA = Negative percent agreement =  $d/(b+d)$

D = unobserved disease status

Unobserved table:

	<b>D=1</b>			<b>D=0</b>		
	<b>R=1</b>	<b>R=0</b>		<b>R=1</b>	<b>R=0</b>	
<b>T=1</b>	a <sub>1</sub>	b <sub>1</sub>		a <sub>0</sub>	b <sub>0</sub>	
<b>T=0</b>	c <sub>1</sub>	d <sub>1</sub>		c <sub>0</sub>	d <sub>0</sub>	

$$Sn(R) = P(R = 1 | D = 1), \quad Sp(R) = P(R = 0 | D = 0)$$

$$Sn(T) = P(T = 1 | D = 1), \quad Sp(T) = P(T = 0 | D = 0)$$

We assume conditional independence of T and R given D.

Let  $\pi = P(D)$  denote the prevalence of the disease.



$$\begin{aligned}
\text{Then } PPA &= P(T = 1 | R = 1) = \\
&P(T = 1 | R = 1, D = 1) \cdot P(D = 1 | R = 1) + \\
&P(T = 1 | R = 1, D = 0) \cdot P(D = 0 | R = 1) = \\
&[Sn(T) \cdot Sn(R) \cdot \pi + (1 - Sp(T)) \cdot (1 - Sp(R)) \cdot (1 - \pi)] / P(R = 1)
\end{aligned}$$

$$\begin{aligned}
\text{Similarly } NPA &= P(T = 0 | R = 0) = \\
&[(1 - Sn(T)) \cdot (1 - Sn(R)) \cdot \pi + Sp(T) \cdot Sp(R) \cdot (1 - \pi)] / P(R = 0)
\end{aligned}$$

In many cases  $\pi$ ,  $Sn(R)$ ,  $Sp(R)$  are (approximately) known.  $PPA$ ,  $NPA$  and  $P(R = 1)$  can be estimated from the observed frequencies. Then one can estimate the sensitivity and specificity of the new test.

An artificial example

	<b>R=1</b>	<b>R=0</b>	
<b>T=1</b>	81	59	140
<b>T=0</b>	39	121	160
	120	180	300

Here  $PPA=0.675$ ,  $NPA=0.672$ ,  $P(R=1)=0.4$

Suppose it is known that the prevalence is  $1/3$ , and the sensitivity and specificity of the reference test are 0.80 and 0.85, respectively.

Then by solving the above equations we estimate that the new test has a sensitivity of 0.80 and a specificity of 0.70.

