Cognition 126 (2013) 87–100

Contents lists available at SciVerse ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/COGNIT

Using regression to measure holistic face processing reveals a strong link with face recognition ability

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ARTICLE INFO

Article history:
Received 21 February 2012
Revised 31 August 2012
Accepted 7 September 2012
Available online 16 October 2012

Keywords:
Face recognition
Face perception
Holistic processing
Individual differences
Composite task
Part-whole task

ABSTRACT

Although holistic processing is thought to underlie normal face recognition ability, widely discrepant reports have recently emerged about this link in an individual differences context. Progress in this domain may have been impeded by the widespread use of subtraction scores, which lack validity due to their contamination with control condition variance. Regressing, rather than subtracting, a control condition from a condition of interest corrects this validity problem by statistically removing all control condition variance, thereby producing a specific measure that is uncorrelated with the control measure. Using 43 participants, we measured the relationships amongst the Cambridge Face Memory Test (CFMT) and two holistic processing measures, the composite task (CT) and the part-whole task (PW). For the holistic processing measures (CT and PW), we contrasted the results for regressing vs. subtracting the control conditions (parts for PW; misaligned congruency effect for CT) from the conditions of interest (wholes for PW; aligned congruency effect for CT). The regression-based holistic processing measures correlated with each other and with CFMT, supporting the idea of a unitary holistic processing mechanism that is involved in skilled face recognition. Subtraction scores yielded weaker correlations, especially for the PW. Together, the regression-based holistic processing measures predicted more than twice the amount of variance in CFMT ($R^2 = .21$) than their respective subtraction measures ($R^2 = .10$). We conclude that holistic processing is robustly linked to skilled face recognition. In addition to confirming this theoretically significant link, these results provide a case in point for the inappropriateness of subtraction scores when requiring a specific individual differences measure that removes the variance of a control task.

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1. Introduction

Holistic face processing has popularly been defined as the simultaneous integration of the multiple features and components of a face into a single perceptual representation (Rossion, 2008). Alternatively, others have conceived of holistic face processing as an obligatory attentional strategy, in which parts are represented independently but are not treated as such during perceptual decision-making (e.g., Richler, Tanaka, Brown, & Gauthier, 2008). Classic demonstrations of holistic face processing include the following phenomena, in which faces show consistently larger effects than objects: (a) face recognition is disrupted when inverting the picture-plane (face inversion effect, Yin, 1969); (b) immediate memory for a face part is much more accurate when that part is presented in the

Abbreviations: CFMT, Cambridge Face Memory Test; CT, Composite task; PW, Part-whole task.

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0010-0277/$ - see front matter Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.cognition.2012.09.004

whole face than when it is presented alone (part-whole task, Tanaka & Farah, 1993); and (c) aligning two half faces of different individuals decreases performance for tasks that require perception of either half independently (composite task, Young, Hellawell, & Hay, 1987). More recently, Van Belle and colleagues (2010) discovered that when a mask covers participants' fixation area, participants show a marked impairment in discriminating inverted faces but are not impaired at upright faces, indicating that participants integrate other information around the masked portion in the upright faces. These works provide rich converging evidence for the existence of holistic face processing.

In addition to the specialized ability to perceptually integrate faces into a coherent whole, neurotypical individuals also have excellent short-term and long-term face memory abilities. For example, visual short-term memory for faces is significantly better than for objects (Curby & Gauthier, 2007). Long-term recognition of faces from memory is extremely accurate and fast, especially for well-known faces (Ramon, Caharel, & Rossion, 2011; Tanaka, Curran, Porterfield, & Collins, 2006), and is robust to perceptual degradation (Liu, Seetzen, Burton, & Chaudhuri, 2003).

It is commonly assumed that face-specific holistic processing abilities underlie our impressive ability to recognize faces. Though several findings are consistent with this possibility, the assumption has yet to receive strong empirical support. First, studies suggest that both holistic face processing and face recognition improve throughout infancy (e.g., Cashon & Cohen, 2003, though both may reach adult levels by age 5, Crookes & McKone, 2009). Such parallel improvements over development, however, are not uncommon even for functionally independent abilities. Second, studies of prosopagnosics, individuals with severe face recognition deficits, have shown that they also have significant deficits in holistic processing of face identity (Busigny, Joubert, Felician, Ceccaldi, & Rossion, 2010; Ramon et al., 2011; DeGutis et al., submitted for publication). Yet while these neuropsychological studies provide a powerful means of dissociating abilities (e.g., face and object processing), their capacity to *associate* impaired abilities is more limited (Caramazza, 1984; though see individual differences approach in DeGutis et al., submitted for publication). Third, reports suggest that the other-race effect, the recognition advantage for own-race compared to other-race faces, co-occurs with an own-race advantage in holistic processing as well as an own-race advantage in processing configural face information (Hancock & Rhodes, 2008; Sporer, 2001). Again, however, these findings could exist in parallel, and are only weak evidence for a functional linkage. Moreover, researchers have largely failed to find significant correlations between the size of an individual's own-race recognition advantage and the size of their own-race holistic processing advantage (e.g., Michel, Rossion, Han, Chung, & Caldara, 2006; though see Rhodes, Brake, Taylor, & Tan, 1989). Such a lack of correlation provides evidence *against* the hypothesis of a functional linkage between holistic processing and the other-race effect in face recognition. Taken together, these previous studies neither strongly support nor strongly falsify the notion that holistic processing plays a role in skilled face recognition.

Three recent studies have examined individual differences in holistic processing and face recognition. A robust individual differences-based correlation between face recognition and measures that isolate holistic processing would provide strong evidence for the presence of a specific functional linkage. However, the results of these three studies differ widely, and it is therefore difficult to draw clear conclusions from them. These studies report nearly the full range of possible non-negative relationships between holistic processing and face memory: zero ($R^2 = 0.003$; Konar, Bennett, & Sekuler, 2010a), non-zero but quite small ($R^2 = 0.02$; Wang, Li, Fang, Tian, & Liu, 2012), and rather sizable ($R^2 = 0.16$; Richler, Cheung, & Gauthier, 2011a). Additionally, these studies have either failed to establish significant associations between multiple measures of holistic processing (Konar, Bennett, & Sekular, 2010b; Wang et al., 2012) or have found a holistic processing/face recognition link only using one holistic processing measure (Richler et al., 2011a), calling into question whether different holistic processing tasks are measuring similar aspects of a unitary holistic construct rather than certain task-specific effects.

Konar and colleagues (2010a, b), the first to gather such data, reported that individual differences in their composite task (CT) did not significantly correlate with performance on a face identification task. In contrast, Richler and colleagues (2011a) demonstrated a sizable positive relationship between face recognition ability and the complete design of the CT, which reduces confounding response bias effects, ostensibly providing a better measure of holistic processing. While this article made a strong case that Konar and colleagues' failure to find a correlation may have resulted from confounding factors in the partial design of the CT, it left open the possibility that this holistic/face recognition link is due to task-specific aspects of the CT rather than holistic processing, per se. Wang and colleagues (2012) most recently added to this debate by showing that face recognition performance, when subtracting object recognition performance, was significantly but quite modestly correlated with both CT (using a similar partial design as Konar et al., 2010a) and part-whole task (PW). Moreover, they demonstrated that PW and CT did not correlate with each other. Wang and colleagues also added to this debate by reporting the reliabilities of their measures, indicating that the relationship between holistic processing and face recognition may be substantially attenuated by the lack of reliability of the measures used.

In sum, while individual differences-based analyses can provide a strong test for a functional linkage (Wilmer, 2008), the results reported to date have either failed to show construct validity for holistic processing, have demonstrated only small holistic processing/face recognition effect sizes, or have not provided converging evidence from multiple measures of holistic processing. Here, we clarify this debate with an improved analytic approach. The above studies all calculated measures of holistic processing by numerically subtracting the control condition (parts trials in PW and misaligned trials or misaligned congruency effect in CT) from the condition of interest (whole trials in

PW and aligned trials or aligned congruency effect in CT) to produce difference scores. As we confirm and illustrate below, such subtraction measures are routinely confounded with the control condition in individual differences studies (Cronbach & Furby, 1970; Edwards, 2001; see Figs. 2E and 3E for demonstrations that PW and CT subtraction measures negatively correlated with control conditions). At best, this confounding complicates the interpretation of the prior individual differences based studies. At worst, one or more of those studies' results may have been a spurious artifact of the decision to use subtraction measures. The current study regresses the control conditions from the conditions of interest, thereby creating specific measures independent of the control condition.

We first test whether regression-based measures of holistic processing (PW and CT) correlate with each other where subtraction-based measures failed to do so (Wang et al., 2012). We next test whether a regression approach can clarify the link between holistic face processing and face recognition ability. Finally, we test the relative contribution of holistic processing and non-holistic processing to face recognition ability.

2. Methods and materials

2.1. Participants

43 Caucasian participants (27 female) with an average age of 24.37 years (SD = 4.71) took part in the study for compensation. All reported having never experienced difficulties with face recognition and having normal or corrected-to-normal vision. All participants gave informed consent in compliance with the Institutional Review Board of the VA Boston Healthcare System and were tested at the VA Boston Medical Center in Jamaica Plain, MA.

2.2. Tasks

2.2.1. Cambridge Face Memory Test

We chose the Cambridge Face Memory Test (CFMT) as our measure of face recognition memory because it has high reliability and validity, and because its wide use affords broad comparability with other studies. Its internal reliability in published studies ranges from .86 to .89 (α = .89, Wilmer et al., 2010; α = .86, Duchaine & Nakayama, 2006; α = .88, Bowles et al., 2009) and its test–retest reliability is .70 (Wilmer et al., 2010). Its high validity is shown by its face specificity: it correlates highly with other face-related measures (naming of famous faces: r = .70, Russell, Duchaine, & Nakayama, 2009, and r = .51, Wilmer et al., 2010; face perception: r = .60, Bowles et al., 2009), yet correlates more modestly with measures of non-face visual memory (r = .26) and verbal memory (r = .17) (Wilmer et al., 2010).

Participants learned to recognize six target faces, excluding non-facial cues that could be used for differentiation (e.g., hair, see Fig. 1A), and were tested in progressively more difficult stages.

During the introductory phase, a target face was presented from three different views (front, right profile, left profile) for 3 s per view. After this, participants were presented with three three-alternative forced-choice trials, where they identified the target face among two foils, with one trial for each of the three views. The process was repeated for the remaining five faces, resulting in 18 total trials. Next, participants studied these same 6 target faces shown all at once for 20 s. Following this study period, participants were tested on 30 trials where they identified a target face among two foils from novel views and with changes in lighting (see Fig. 1A top). Participants then received 20 more seconds to study the same 6 target faces. The remaining 24 trials were the most difficult and presented faces with novel views, lighting changes, and the addition of visual noise (see Fig. 1A bottom).

2.2.2. Part-whole task

To measure holistic processing, we used a recent version of the classic PW task (Tanaka, Keifer, & Bukach, 2004, used with permission of Jim Tanaka, University of Victoria).

2.2.2.1. Logic of the task. The part-whole task assesses how much subjects integrate individual facial features into the

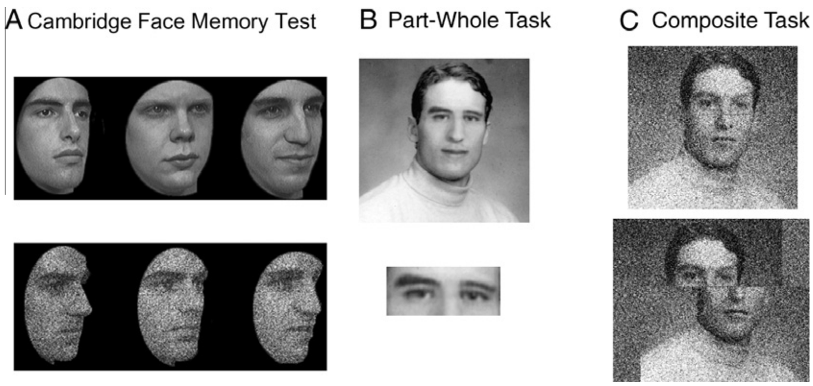

Fig. 1. Example of task stimuli for CFMT (A), part-whole (B), and composite task (C). In A are example test trials with view change (top) and the addition of noise (bottom) in CFMT. The participant's task is to choose which of the three faces is a target face that they were asked to remember. In B are example stimuli for whole and part trials in the part-whole task. In C are example aligned and misaligned stimuli in the composite task. Note that these composite task stimuli are the same as those used in the part-whole but with the addition of 30% noise.

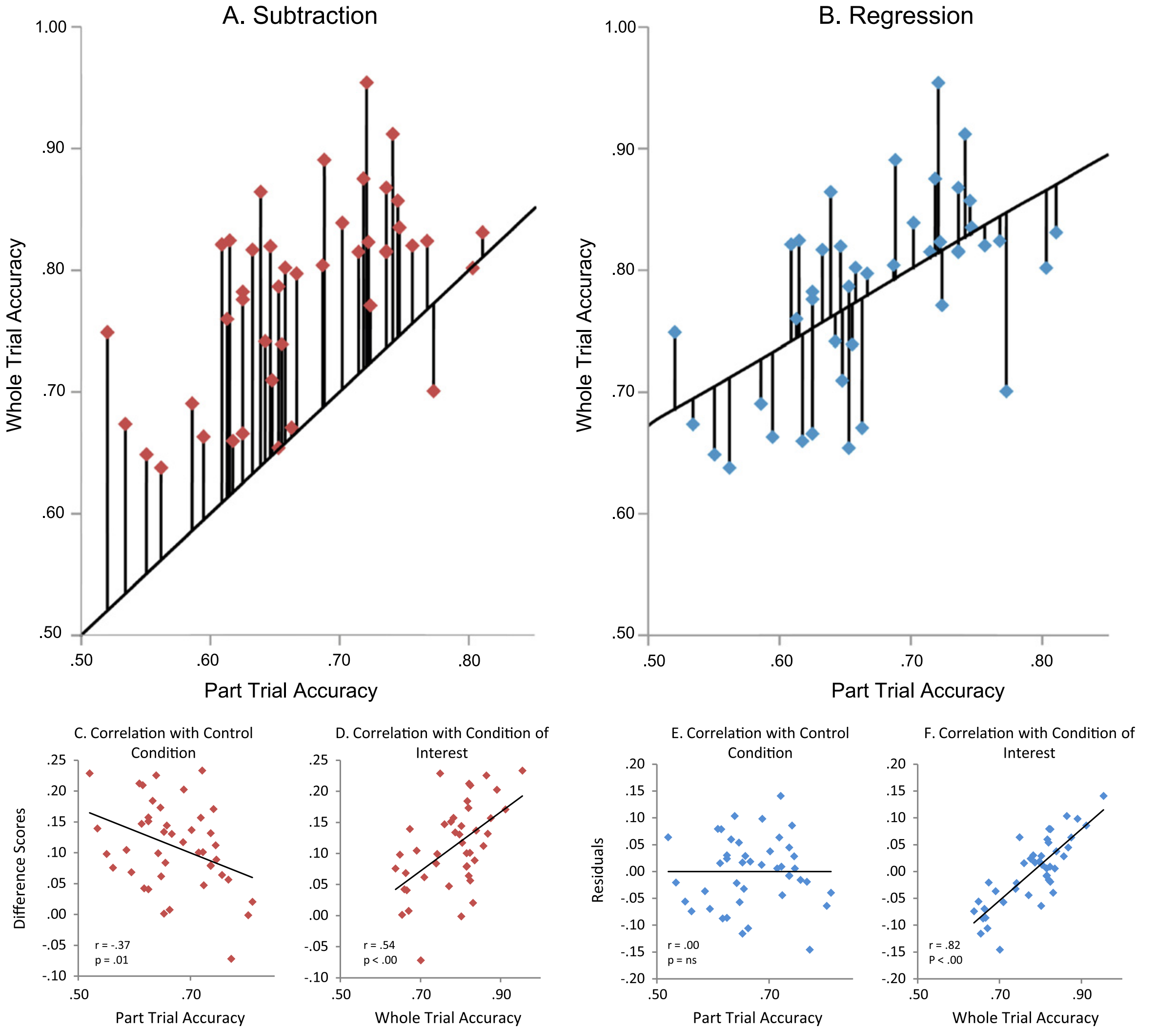

Fig. 2. Holistic processing measurements for PW using subtraction and regression. Part trials serve as the control condition, while whole trials serve as the condition of interest. Individual differences in holistic processing were calculated two ways: (A) subtraction, where the control condition is subtracted from the task of interest to produce a difference score (left half, red plots, each difference score is indicated with a vertical black line) or (B) regression, where the control condition is regressed from the task to interest to produce residuals (right half, blue plots, each regression residual is indicated with a vertical black line). As can be seen in the lower left graphs, the subtraction approach creates a measure that is negatively correlated with the control condition and positively correlated with the condition of interest. In contrast, the regression approach creates a measure that is not correlated with the control task but is strongly correlated with the condition of interest.

whole face context. In particular, after encoding a target face (e.g., Roger's face), subjects demonstrate an advantage for discriminating a feature change (e.g., discriminating Roger's nose from Ken's nose) when features are shown within the context of the target face (whole trials) compared to when discriminating features shown in isolation (part trials). Our logic was that between-subjects variation in part trials primarily reflects general visual perception as well as face part processing abilities, whereas between-subjects variation in whole trials reflects general visual perception, face part processing, and holistic face processing abilities. Thus, we reasoned that regressing part trial performance from whole trials would provide a relatively pure measure of holistic face processing (for further details see analysis Section 2.3.1, below).

2.2.2.2. Stimuli and procedure. Target faces were created using either a Caucasian male or Caucasian female face template that included the hair and face outline. For each male and female template, six target faces were created, each with a different nose, mouth, and pair of eyes inserted into the template (for an example, see Fig. 1B). Therefore, each target face was unique and did not share a feature with another target face. Foils for each target face were created by switching one of the three facial components (eyes, nose, or mouth) with that of a different target face.

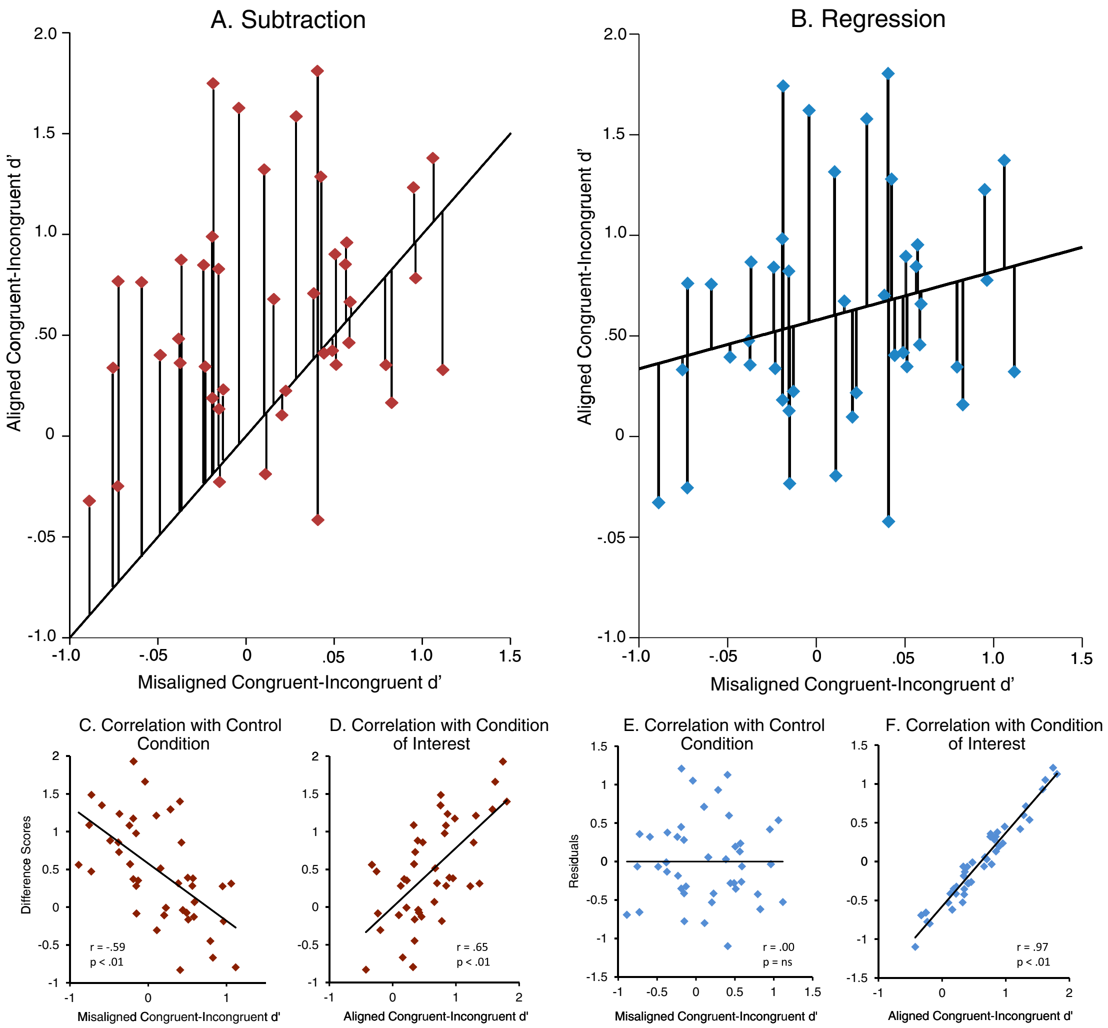

Fig. 3. Holistic processing measurements for the CT using subtraction and regression. The congruency effect in misaligned trials serves as the control effect while the congruency effect in aligned trials serves as the effect of interest. Individual differences in holistic processing were calculated two ways: (A) subtraction, where the control effect is subtracted from the effect of interest to produce a difference score (left half, red plots, each difference score is indicated with a vertical black line) or (B) regression, where the control effect is regressed from the effect of interest to produce residuals (right half, blue plots, each regression residual is indicated with a vertical black line). As can be seen in the lower left graphs, the subtraction approach creates a measure that is negatively correlated with the control effect and positively correlated with the effect of interest. In contrast, the regression approach creates a measure that is not correlated with the control effect but is strongly correlated with the effect of interest.

For each trial in PW, participants were initially presented with a central fixation for 500 ms. A whole target face was then centrally presented for 1000 ms, followed by a mask (scrambled face) for 500 ms. Next, participants were presented with either a whole trial, in which one stimulus was the target face and the other a foil, or a part trial, in which only a given isolated feature (eyes, nose, or mouth) from both the target and foil face were presented. On whole trials (50%) participants were asked to indicate which whole face matched the target face, and for part trials (50%) participants were asked to indicate which isolated face feature matched the target face. For both part and whole trials, the stimuli were presented side by side and remained on the screen until the participants made a response of '1' for the left stimulus or '2' for the right stimulus. There was a single session of 72 trials for each gender (36 parts trials and 36 whole trials), with equal numbers testing eyes, nose, and mouth, with gender being blocked.

2.2.3. Composite task

Because of its wide use and acceptance as a measure of holistic face processing, we chose the CT as our second measure of holistic processing (see Fig. 1C).

2.2.3.1. Logic of the task. In the composite task, subjects are slower and less accurate to say that the top halves of two sequentially presented faces are the same when aligned with different bottom halves, compared to either when the top halves are aligned with same bottom halves

(Richler, Mack, Gauthier, & Palmeri, 2009) or when the halves are misaligned (Hole, 1994). In essence, the CT primarily uses interference as a measure of holistic processing – the irrelevant lower half of the face affects upper half discrimination performance because the face is automatically processed as a whole.

There exists a debate in the literature about the relative validity of two different versions of the CT, the complete design and the partial design (e.g., Richler et al., 2011a). Since the complete design of the CT has shown to eliminate the confound between the effect of alignment and response bias that may occur in the partial design (Cheung, Richler, Palmeri, & Gauthier, 2008; Richler, Cheung, Wong, & Gauthier et al., 2009), and as a result may better capture face-specific holistic processing effects (Gauthier, Klaiman, & Schultz, 2009; Richler, Bukach, & Gauthier, 2009), we used it instead of the more common partial design (e.g., Konar et al., 2010a, 2010b; Wang et al., 2012). For more a thorough description of the details of the partial and complete designs the reader is referred to Richler et al. (2011a).

The logic of the complete design is that the difference in performance between aligned congruent and aligned incongruent trials reflects holistic face processing while the difference in performance between misaligned congruent and misaligned incongruent trials does not. In particular, when the task is to determine if the top halves of two sequentially presented faces are the same, holistic processing is thought to cause subjects to perform worse on trials with same top halves and different bottom halves (incongruent trials) and slightly better on trials with same top halves and same bottom halves (congruent trials). In contrast, the difference in performance between misaligned congruent and misaligned incongruent trials is not thought to reflect holistic face processing, though it may reflect context effects driven by non-face-specific mechanisms (Gauthier et al., 2009; Richler, Bukach, & Gauthier, 2009).

Considering this, our logic was that between-subjects variation in the congruency effect (congruent minus incongruent trials) in misaligned trials might reflect non-face-specific context effects, whereas between-subjects variation in the congruency effect in aligned trials reflects both non-face-specific context effects as well as holistic face processing abilities. Thus, we reasoned that regressing the misaligned congruency effect from the aligned congruency effect would leave a relatively pure measure of holistic face processing (for further details see analysis Section 2.3.1, below).

2.2.3.2. Stimuli and procedure. Faces in the CT were the same as those used in the part-whole task. The orders of the PW and CT were counterbalanced across subjects. The images were split into a top half and a bottom half with a horizontal 2 pixel slit, approximately in the middle of the nose, creating aligned faces. To create misaligned faces, the bottom half was shifted to where the face outline of the bottom image lined up with the nose midline of the top. Pilot testing using the same faces as PW revealed ceiling effects during misaligned trials, so 30% Gaussian noise was added to the faces to increase difficulty. Because the part-whole stimuli were all based on one female and one male face with the same chin, hair, eyes, and head shape, all male composite faces had identical outer features and all female composite faces also had identical outer features.

Participants saw two sequentially presented faces and were told to selectively attend to the top portion of the face and report, as accurately and quickly as possible, if the top halves were the same or different. Each trial began with a 300 ms fixation cross, followed by a 200 ms blank screen, then the target face for 400 ms. Participants were then presented with a mask image (as in the part-whole task) for 500 ms. The test face was then presented for 400 ms followed by a prompt for a response (unlimited duration), with a 1 s interval before the next trial. Each trial began with one of the six template faces, followed by a face from one of the four conditions (same/different × congruent/incongruent). For each gender, the task had two rounds of 72 trials, with a break between each round, with gender being blocked. There were equal numbers of aligned and misaligned trials in each block, with each alignment having an equal number of trials in each condition (18). In addition, there were a balanced number of same and different trials.

2.3. Analyses

2.3.1. Calculating difference scores and residuals for PW and CT

For the part-whole and composite tasks, we calculated holistic processing scores using both subtraction, as was used in prior studies (Konar et al., 2010a; Richler et al., 2011a; Wang et al., 2012), and regression, which we advocate here as the more informative approach.

The disadvantage of subtraction scores in individual differences-based analyses is that they are yoked to their two component scores in a way that obscures the relative contribution of each component to their variation. In the case of the part-whole task (see Fig. 2), a low subtraction score could result entirely from exceptional performance in the part condition, entirely from poor performance in the whole condition, or from some combination of the two. Likewise, a correlation (or lack thereof) between part-whole subtraction scores and face recognition could result entirely from variation in the part condition, entirely from variation in the whole condition, or from some combination of the two. Given that holistic processing is theorized to be present in whole trials but absent in part trials, a correlation (or lack thereof) resulting from variation in the part trials is not of theoretical interest. The presence of parts variation in the part-whole task subtraction score therefore prevents one from asking the focused question of interest: Does variation in holistic processing, which is only theorized to be present in the wholes condition, relate to face recognition?

Regression scores, in contrast to subtraction scores, contain only the variation in the condition of interest, with the variation in the other condition statistically removed. For example, regression measures holistic processing in the part-whole paradigm as the variation left over in whole trials (the condition of interest) after the variation it shares with the part trials (the control condition) is removed. Regression accomplishes this by essentially asking how a given individual's whole trial performance compares to the typical person with the same part trial performance. This can be clearly visualized in Fig. 2B. In this figure, whole trial performance is plotted against part trial performance, and the least-squares regression line shows the expected whole performance for someone with any given part performance. The distance of each dot above or below this line represents how each individual's whole performance deviates from the best estimate of the mean whole performance for all other individuals with the same part score. In this way, a regression measure is created that statistically equates all individuals' part scores and measures that portion of their whole performance that is not accounted for by their part performance.

The computation of subtraction can be similarly represented on a figure that plots the condition of interest against the control condition. For example, Fig. 2A, like Fig. 2B, plots wholes performance against parts performance. Instead of plotting the regression line, however, Fig. 2A plots the line of equality representing all the points where the subtraction score would be zero. The vertical distance of each point from this line represents that individual's subtraction score. The variation that our subtraction scores share with their control measures is documented by the non-zero correlation shown in the bottom left graph in Fig. 2C. In contrast, Fig. 2E shows that the regression scores are statistically independent of their respective control measures.

Note that while individual regression scores have a particular meaning relative to their least-squares regression lines, and subtraction scores have a particular meaning relative to their subtraction lines, the variance in these scores across individuals remains the same with any arbitrary vertical translation of these lines. Therefore, for purposes of correlational analyses, the difference in slope between the regression and subtraction line is what differentiates these two measures.

Though the CT measures holistic processing by comparing two effects (aligned congruency effect vs. misaligned congruency effect) rather than two conditions (as in the PW), these same principles apply. In particular, the standard way of calculating holistic processing in the CT (shown in Fig. 3A) is by subtracting the misaligned congruency effect (misaligned congruent–misaligned incongruent) from the aligned congruency effect (aligned congruent–aligned incongruent). Note that these are in fact "difference of differences" scores that subtract one difference score from another. As can be seen in Fig. 3C and D, these differences of differences correlate with the congruency effect for both misaligned (control condition) and aligned trials (condition of interest). This illustrates that, when using the standard subtraction approach, both misaligned and aligned congruency effects contribute to the holistic processing measure. Unfortunately, this fails to capture the theory of the CT that holistic processing influences the aligned congruency effect but not the misaligned congruency effect (for an explanation of this theory, see Section 2.2.3.1 above).

In contrast, the regression-based holistic processing measure correlated with the aligned congruency effect (Fig. 3F) but not the misaligned congruency effect (Fig. 3E), better capturing the theory behind the CT. To calculate this regression-based holistic processing measure, we dropped one level of subtraction but retained the other. Specifically, we calculated the same misaligned congruency measure (misaligned congruent minus misaligned incongruent) and the same aligned congruency measure (aligned congruent minus aligned incongruent) as Richler and colleagues (2011a), using subtraction, but then regressed the misaligned measure from the aligned measure (see Fig. 3B). The theoretical reason for this hybrid "regression of differences" approach is that we expected holistic processing to *both* improve performance in the aligned congruent condition and hinder performance in the aligned incongruent condition. In cases such as this, where both conditions are predicted to have non-zero effects and the directions of these predicted effects are opposite in sign, a subtraction measure may capture the desired effects under the assumption that the magnitude of those opposite effects is comparable. An additional benefit of this hybrid approach is that then there was only a single stage of computation changed between the subtraction ("difference of differences") measure and the regression ("regression of differences") measure. Any variation in results between the subtraction CT and regression CT measure could therefore be attributed to this single change.

Note that results are similar, and all key conclusions remain supported, if a "regression of regressions" holistic processing measure is used in place of a "regression of differences" measure (see Supplementary Materials). The "regression of regressions" measure is computed by regressing the misaligned congruency regression scores (residuals obtained by regressing misaligned incongruent from misaligned congruent) from the aligned congruency regression scores (residuals obtained by regressing aligned incongruent from aligned congruent).

3. Results

3.1. Face recognition and holistic face processing: overall performance

We first sought to confirm that our results are in line with previous reports and that PW and CT show robust holistic processing effects (see Fig. 4).

The results of CFMT demonstrate a very similar mean and standard deviation to previous findings (raw score $M = 58.8$, $SD = 8.4$) (Duchaine & Nakayama, 2006; Wilmer et al., 2010). Additionally, we found very similar results to a previous study of Caucasian participants on PW (Tanaka et al., 2004), demonstrating a robust whole over part trial advantage (whole $M = 78.2\%$, part $M = 67.1\%$, $t(42) = 10.50$, $p < .0001$). We did not find a significant part vs. whole difference in reaction times, suggesting that this effect was not driven by a speed-accuracy tradeoff. For CT, similar to previous reports (Richler et al., 2011a), we showed a significant congruency by alignment interaction ($F(1, 42) = 21.73$, $p < .0001$) driven by decreased performance on aligned incongruent trials relative to misaligned incongruent trials ($t(42) = 4.76$, $p < .001$). We did not find a significant congruency by alignment interaction in reaction times, suggesting that this effect was not driven by a speed-accuracy tradeoff.

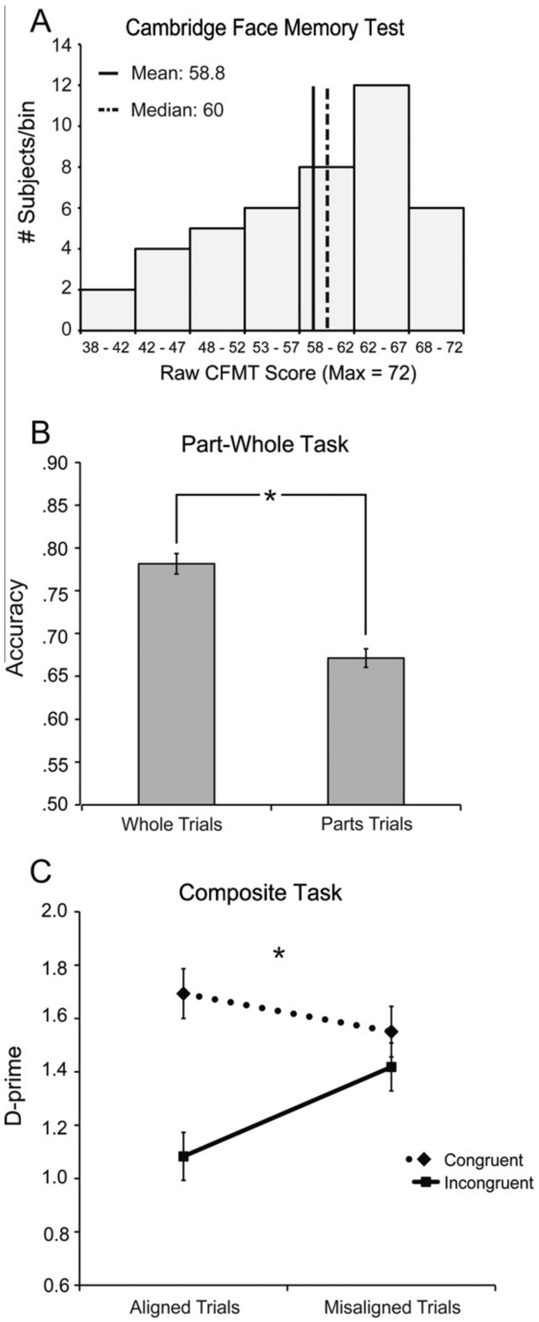

Fig. 4. Results of the Cambridge Face Memory Test (A), part-whole task (B), and composite task (C). The asterisk in the part-whole task indicates a significant difference between part and whole trials ($p < .05$) and the asterisk in the composite task indicates a significant alignment by congruency interaction ($p < .05$).

3.2. Reliability of face recognition ability and measures of holistic face processing

Because our individual differences correlations will scale with the reliability with which they are measured, it is necessary to consider differences in reliability when comparing the magnitude of these correlations. An informative statistic is the theoretical upper bound on a correlation. Computed as the geometric mean of the reliabilities of the measures being correlated (Schmidt & Hunter, 1996), the upper bound is the correlation that would be expected between these measures, once measurement error is taken into account, if their true correlation was 1.0. Correlations scale proportionally with this upper bound. For example, the same underlying relationship that produces a 0.2 correlation with an upper bound of 0.4 would be expected to produce a 0.3 correlation with an upper bound of 0.6 and a 0.5 correlation if it were possible for the upper bound to reach 1.0 (Schmidt & Hunter, 1996).

Table 1 summarizes the results of our reliability analysis (for additional rationale and details of methods, see Supplementary Materials). The first column in Table 1 shows the reliability of each measure, including each separate condition in each task. As Table 1 shows, CFMT has high reliability ($\lambda 2 = .88$) and the separate conditions in PW and CT have fairly good reliability (all $\lambda 2$'s > .5, see Table 1). As expected, the difference scores and residual scores were overall less reliable (all $\lambda 2$'s < .31, Table 1) (Peter, Gilbert, Churchill, & Brown, 1993). However, the residual scores were considerably more reliable than the difference scores and correspondingly had substantially higher upper bound correlations with CFMT (Table 1).

Columns 2 and 3 show each measure's observed correlation with CFMT and the upper bound of those correlations (see Section 3.4 below). We also calculated the upper bound correlations between PW and CT holistic processing measures and found them to be .08 for the subtraction approach and .27 for the regression approach. Note that some of the correlations we report in Table 1 and below exceed their estimated upper bound. This is not as paradoxical as it may at first seem, because both the correlations and the upper bound are estimated with some margin of error.

3.3. Holistic processing measures correlate with each other

After assessing the reliabilities of our measures, we next sought to determine if the measures of holistic processing are significantly related to each other. We first correlated PW and CT holistic processing subtraction measures with each other, and, similar to previous reports by Wang et al. (2012) and Konar et al. (2010b) using subtraction, found no significant relationship between these measures (see Fig. 5, PW vs. CT complete analysis: $r = .23$, $p = .14$; PW vs. CT partial analysis: $r = .06$, $p = .70$, see more on partial analysis below). However, when using the regression approach, PW and CT holistic processing scores *did* significantly correlate with each other (see Fig. 5, $r = .44$, $p < .005$), suggesting that they measure overlapping aspects of holistic processing. For completeness we also correlated the residuals of CT with the difference scores of PW ($r = .28$, $p = .09$) and the difference scores of CT with the residuals of PW ($r = .35$, $p < .05$).

After finding a highly significant relationship between CT and PW holistic processing using the regression approach, we sought to further probe the different methods of analyzing the CT in order to determine whether the CT's relationship with the PW is driven more by the

Table 1
Measurement reliability and correlation with CFMT. Reliabilities are Guttman's λ2 with Cronbach's α in parentheses. Upper bound is the highest possible correlation, given the reliability of the two measures. Upper bound is calculated as the square root of the product of the two measures' reliabilities. HP-holistic processing.

	Reliability λ2 (α)	CFMT Correlation	Upper Bound With CFMT
Cambridge Face Memory Test	.88 (.88)	–	–
Part-whole task			
Whole trials	.70 (.65)	**.63***	.79
Part trials	.52 (.43)	**.44***	.67
HP-differences scores	.10 (−.06)	.27	.30
HP-residuals	.31 (.19)	**.46***	.52
Composite task			
Aligned			
Congruent	.72 (.67)	**.50***	.80
Incongruent	.69 (.60)	.21	.78
Misaligned	.84 (.81)	**.43***	.86
Congruent	.74 (.70)	**.35***	.81
Incongruent	.72 (.68)	**.43***	.80
HP-differences scores	.10 (−.06)	**.33***	.30
HP-residuals	.24 (.10)	**.36***	.46

Note: Bold and * indicates that $p < .05$

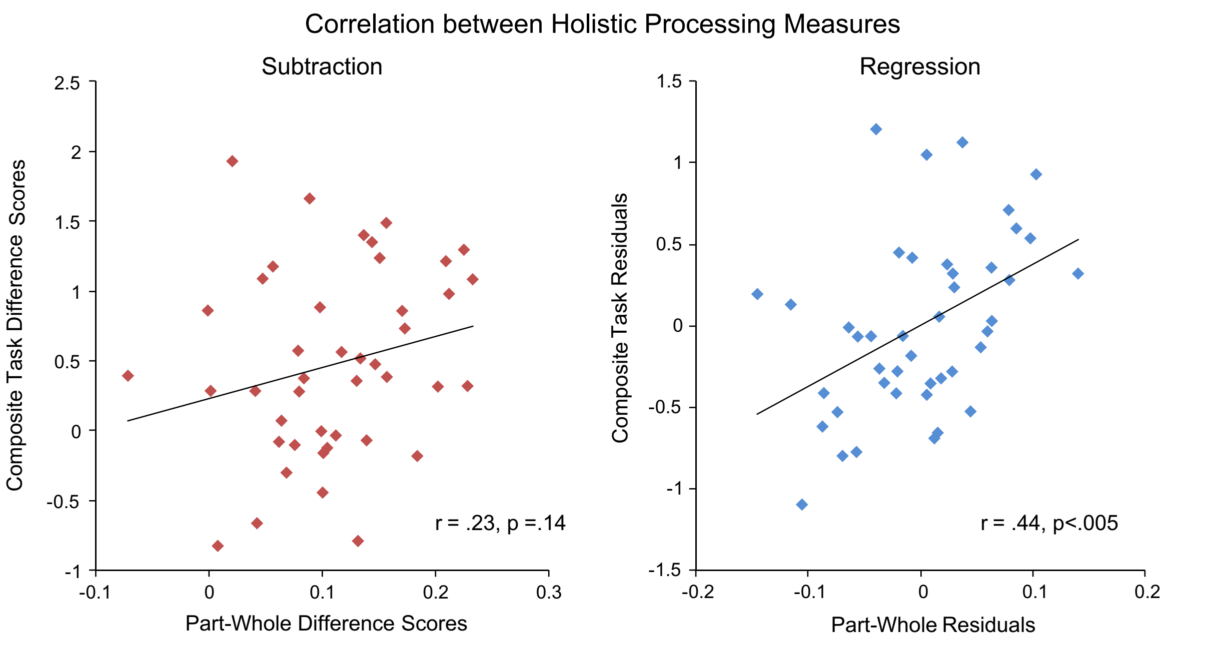

Fig. 5. Correlation between holistic processing measures correlations between holistic processing measures (CT and PW) using subtraction and regression.

congruency effect in aligned trials (aligned congruent minus aligned incongruent, advocated as a measure of holistic processing by Richler, Mack, et al., 2009) or by the commonly used partial analysis effect (misaligned incongruent same trials vs. aligned incongruent same trials). Consistent with the idea that the congruency effect in aligned trials is a good measure of holistic processing, we found a strong correlation between the PW holistic advantage and the CT congruency effect for aligned trials (PW residuals: $r = .43$, $p < .005$; PW difference scores: $r = .28$, $p = .07$) but not misaligned trials (PW residuals: $r = .004$, $p > .9$; PW difference scores: $r = .0003$, $p > .9$). On the other hand, the partial effect analysis of the CT did not show a significant relationship with PW holistic advantage scores when measuring the partial effect using regression (PW residuals: $r = .19$, $p = .21$; PW difference scores: $r = .10$, $p = .51$) or subtraction (PW residuals: $r = .23$, $p = .14$; PW difference scores: $r = .06$, $p = .70$). This lack of a significant relationship between the PW and CT when using the partial analysis replicates previous findings of Konar et al. (2010b) and Wang et al. (2012). Together, these results suggest that the congruency effect in aligned trials drives the significant relationship between the CT and PW rather than the partial effect.

3.4. Holistic face processing is strongly related to face recognition ability

Now that we have established that our tasks are measuring similar aspects of holistic face processing, we turn to quantifying the relationship between holistic face processing and face recognition ability. As can be seen in Fig. 6, when using a subtraction approach only CT significantly correlates with CFMT ($r = .33$, $p < .05$) and there is only a trend towards a significant relationship between PW and CFMT ($r = .26$, $p = .09$). This significant correlation of CT with CFMT using the subtraction approach with the complete design replicates recent work by Richler et al. (2011a). Additionally, the lack of a significant correlation of PW with CFMT using subtraction replicates the results of Konar and colleagues (2010a, 2010b). In contrast to the subtraction approach results, when using the regression approach both PW and CT show strong and significant relationships with CFMT, indicating that greater holistic processing correlates with greater face recognition ability (PW: $r = .46$, $p < .005$; CT: $r = .36$, $p < .05$). The substantially diminished relationship of PW with CFMT using the subtraction approach is likely because it creates a holistic measure that is significantly negatively correlated with the control condition ($r = -.37$, $p < .05$, see Fig. 2C), whereas the regression measure shows zero correlation with the control condition (see Fig. 2F).

The similar regression and subtraction results for CT suggest that when using the complete design of CT, contamination with control task variance ($r = -.59$, $p < .05$, see Fig. 3C) has a relatively modest end result. However, the regression approach still has an advantage over the subtraction approach in that we have a better understanding of the source of the variance in our holistic processing measure. In particular, for the regression approach, we know that the significant correlation of CT with CFMT is driven by the theoretically relevant congruency effect in aligned trials, and not by the (regressed out) congruency effect in misaligned trials. In contrast, for the subtraction approach, the relative contributions of the aligned and misaligned trials are obscured by the subtraction computation, and therefore the subtraction results are more difficult to interpret (Edwards, 2001).

To further characterize the relationship between measures of holistic processing and face recognition, we compared two multiple regressions predicting CFMT, one with PW and CT holistic processing regression scores and the other with PW and CT subtraction scores (see Table 2A). Though both models significantly predicted CFMT, the adjusted R^2 for the regression based measures (.21) was twice as large as the adjusted R^2 for the subtraction based measures (.10), indicating that holistic processing computed by regressing out control tasks better predicts face recognition ability.

In the model containing the regression-based holistic processing measures of PW and CT, PW predicted CFMT variance above and beyond the variance that PW shared with CT. Even after entering the CT into the regression equation first, adding the PW demonstrated a significant R^2 change (R^2 change = .12, $p < .05$). This suggests that the PW may capture aspects of holistic processing that CT does not. Alternatively, some researchers believe that sensitivity to processing configural information is a separate ability from holistic processing (e.g., Maurer, Grand, & Mondloch, 2002; though see Rossion, 2008 for a different view) and the PW may, in addition to measuring holistic processing, measure aspects of this configural processing ability whereas the CT does not. Finally, CT may have explained greater, more PW-independent variance in CFMT if our CT had more closely matched the timing and stimulus format of Richler, Cheung, and Gauthier (2011b).

3.5. Non-holistic processing independently predicts face recognition ability

To clarify whether individual differences in holistic face processing are the main determinant of face recognition ability, we also measured whether non-holistic mechanisms are also related to face recognition ability. To accomplish this, for PW we calculated the relationship of CFMT (a) with overall part trials, (b) with the overlapping variance between part and whole trials, and (c) with the variance in part trials that is independent from whole trials. To calculate the overlapping variance between part and whole trials, we took the overall part trial performance and subtracted the variance in part trials that did not overlap with whole trials. To calculate the variance in part trials that is independent from whole trials we regressed whole trials from part trials. Overall part trial performance was significantly correlated with CFMT ($r = .44$, $p < .005$) and interestingly, the variance in part trials that overlaps with whole trials was highly correlated with CFMT ($r = .63$, $p < .001$), whereas the variance in part trials independent of whole trials was not ($r = -.09$, $p = .85$). In other words, the aspect of part trial performance that is related to face recognition ability is that which overlaps with performance when shown the whole face. This likely reflects general object discrimination abilities engaged by both part and whole trials.

To obtain a measure of non-holistic discrimination ability in CT, we used participants' overall performance on misaligned trials. This is the same approach taken to measure non-holistic processing in the complete design CT as Richler et al. (2011a). In doing so we found that misaligned trials significantly correlated with CFMT (see Table 1, misaligned trials: $r = .43$, $p < .005$), further reinforcing the non-holistic processing/face recognition association.

Finally, to test whether non-holistic and holistic processing predict unique or overlapping aspects of face recognition ability, we ran multiple regressions with non-holistic processing and holistic processing predicting CFMT (see Table 2). A previous report using a similar analysis showed that holistic processing, as measured by CT, significantly independently predicted CFMT accuracy but that non-holistic processing did not (Richler et al., 2011a). In contrast to these results, for PW we found that both part trials and holistic processing significantly independently predicted CFMT performance (see Table 2B). This was true regardless of whether subtraction or regression measures of holistic

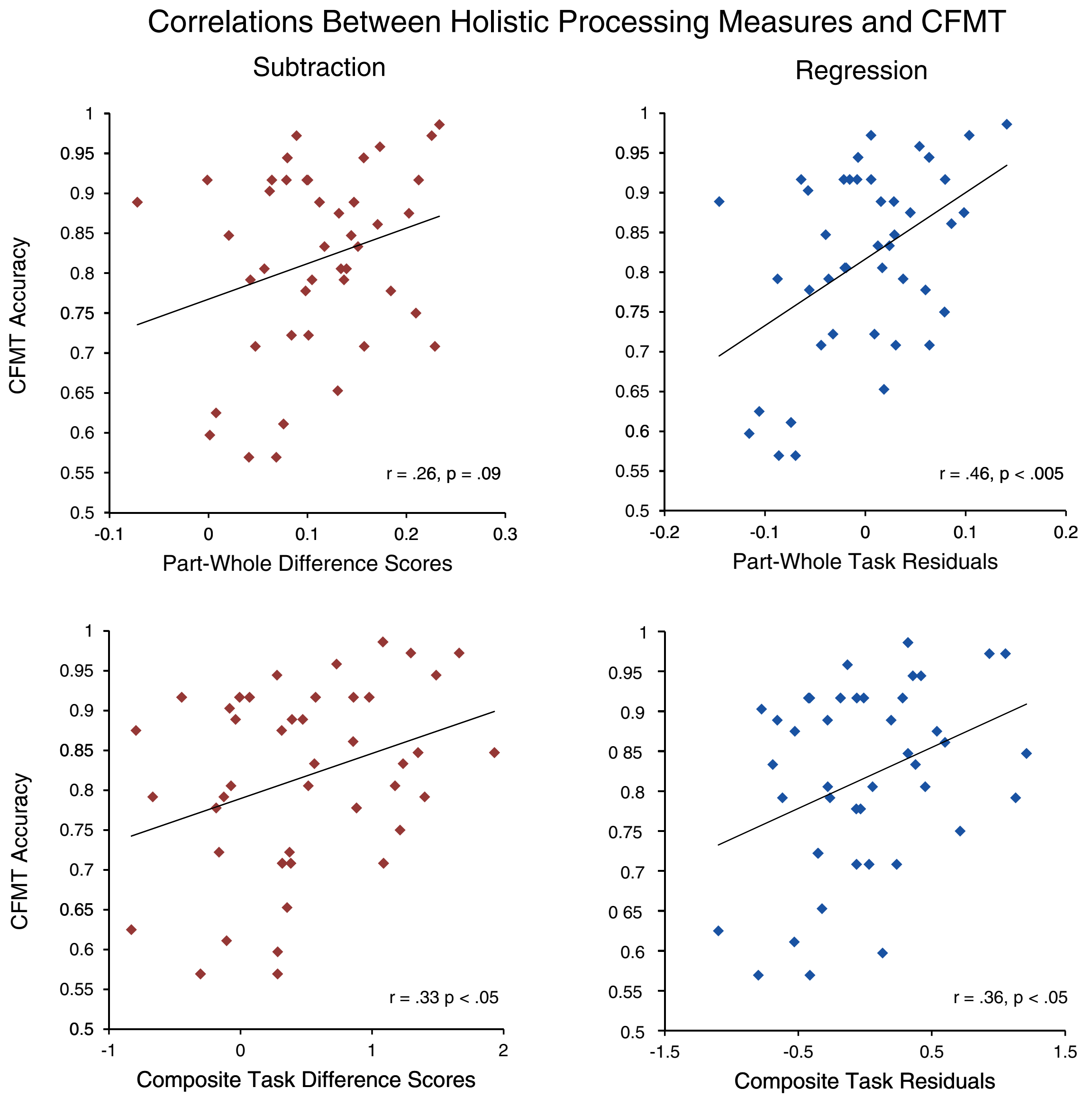

Fig. 6. Correlations between holistic processing measures and CFMT correlations between face recognition ability (CFMT) and both part-whole (top row) and composite task (bottom row), using subtraction (left column) and regression (right column).

processing were used and this was also true if we used the variance in part trials that overlaps with whole trials as our measure of parts processing (see above). For CT, we found similar results when using misaligned trials and CT holistic processing as predictors (see Table 2C). Both independently predicted CFMT performance and again this was true for both the subtraction and regression measures. Taken together, this provides compelling evidence that both holistic processing and non-holistic processing uniquely contribute to face recognition ability.

4. Discussion

The current results demonstrate that holistic face processing measures significantly correlate with each other and with an established measure of face recognition ability. In contrast to previous work in this area, we compute specific measures that isolate holistic processing by regressing out the influence of well-matched control conditions. While prior studies included such control conditions, they did not statistically remove their influence. Rather, they computed subtraction measures that are confounded with the control condition in an individual differences context. Together, these findings place the construct of holistic face processing and the connection between holistic face processing and face recognition ability on solid ground, helping to clarify the recent debate in this literature (Konar et al. 2010a, 2010b; Richler et al. 2011a; Wang et al., 2012). The results also show that holistic face processing and non-holistic processing independently

Table 2
Multiple regressions predicting CFMT. The results of 6 multiple regression models (across in columns) predicting CFMT score. The first two models (A) predict CFMT scores from part-whole and composite task holistic processing scores calculated either via subtraction or regression. The next two models (B) predict CFMT scores from part-whole part scores and holistic advantage scores calculated via subtraction or regression. The final two models (C) predict CFMT scores from composite misaligned scores and holistic processing scores calculated via subtraction or regression. β-standardized beta.

	A. Part-Whole & Composite Task Holistic Processing				B. Part-Whole Holistic Processing & Part Trials				C. Composite Task Holistic Processing & Misaligned Trials			
	Subtraction		Regression		Subtraction		Regression		Subtraction		Regression	
Predictor	β	p	β	p	β	p	β	p	β	p	β	p
Part-Whole:												
Difference Scores	.20	.19			**.50***	.00						
Residuals			**.38***	.02			**.46***	.00				
Part Trials					**.63***	.00	**.44***	.00				
Composite:												
Difference Scores	.28	.07							**.31***	.03		
Residuals			.19	.22							**.31***	.03
Misaligned Trials									**.42***	.00	**.39***	.01
R^2 (adjusted)	**.10***		**.21***		**.38***		**.38***		**.24***		**.25***	

Note: Bold and * indicates that $p < .05$

predict face recognition ability, suggesting that holistic processing is not the sole determinant of face recognition ability.

This study illustrates the advantage of regression over subtraction for isolating individual differences in specific face processing mechanisms. First, using regression to calculate holistic processing produced more valid measures in that they did not correlate with the control task (see Figs. 2E and 3E), whereas using subtraction showed significant negative correlations with control tasks (see Figs. 2C and 3C). This illustrates a theoretical assumption of the subtraction approach that is typically not intended by the researcher. This assumption becomes evident after inspecting the way a subtraction is computed. Subtraction linearly combines the negative control condition variance (e.g., part trials in PW) with the positive variance from the condition of interest (e.g., whole trials in PW). Given that subtraction weights the contribution of the control condition equally and oppositely to the contribution of the condition of interest, it is not surprising that the resulting subtraction measures correlated negatively with the control condition. In contrast, the regression approach mathematically factors out the control condition so that its variance has no contribution to the measurement of interest, which is what the researcher typically intends of a control condition. This creates a more specific, more theoretically interpretable measure. For example, in the current results the CT subtraction holistic processing measure significantly correlated with CFMT. However, there could be several ways this could mathematically arise, many of which are theoretically uninterpretable. In contrast, by using regression we constrained the source of variance in our CT holistic processing measure, and though we obtained similar CFMT correlations to the subtraction approach, we can be confident that these results are theoretically relevant. As well as being more valid, regression measures also showed greater reliability than subtraction measures (see Table 1), likely because regression measures did not include noise from the control tasks.

In providing more valid and reliable measures of holistic processing, the regression approach illuminates the holistic face processing/face recognition debate in several important ways. First, it demonstrates a strong correlation between PW and CT holistic measures, supporting the idea that holistic face processing is a unitary construct (Farah, Wilson, Drain, & Tanaka, 1998; Rossion, 2008) rather than a collection of distinct task-specific processes (e.g., Wang et al., 2012). The strong relationship between these tasks, despite that the PW measures holistic processing by an enhancement effect and the CT by an interference effect, supports the notion that holistic face processing involves both the interdependence among facial components (PW) as well as processing the whole face in an obligatory fashion (CT) (Farah et al., 1998; Richler, Cheung, et al., 2009 Rossion, 2008). The current study also adds to existing evidence that holistic processing is robust over time (see Richler, Mack, et al., 2009) as we observe the PW/CT correlation despite these tasks having different stimulus durations (1000 ms presentation in PW, 400 ms presentation in CT). The current findings further demonstrate that holistic processing as measured by PW residuals is most related to the aligned congruency effect in the CT (aligned congruent minus aligned incongruent trials), advocated by Richler and colleagues (Richler, Mack, et al., 2009), and is less related to the more commonly reported CT partial effect (misaligned incongruent same minus aligned incongruent same trials). This suggests that the complete design provides a preferable holistic processing measure to the partial design. Considering this, Konar et al. (2010b) and Wang's et al. (2012) failure to find a significant PW/CT link may be because they used subtraction rather than regression to measure the PW holistic advantage and also because they employed the partial design of the CT rather than the complete design. Taken together, the current results reinforce that there exists a reliable, robust, and unitary holistic face processing mechanism that is consistent with both current (Rossion, 2008) and more classic conceptions of holistic face processing (Farah et al., 1998).

Not only do the present regression-based results support the construct of holistic face processing, they also reinforce the connection between holistic processing and face recognition ability. Our two holistic processing measures, when calculated via regression, each significantly predicted face recognition ability, and together explained 21% of the variance in face recognition ability. In contrast, when calculated via subtraction, only CT significantly predicted face recognition ability, and the two holistic processing measures together only explained 10% of the variance in face recognition ability. Likewise, these effect sizes are much larger than those recently reported by Wang and colleagues (2012) using difference scores (current results: PW $R^2 = .21$, CT $R^2 = .13$; Wang et al., 2012: PW $R^2 = .02$, CT $R^2 = .02$). These larger effect sizes enabled us to find significant effects with a substantially smaller sample size (current study: 43 participants; Wang et al., 2012: 337 participants), confirming that regression is a more powerful approach than subtraction and may allow researchers to perform effective individual differences analyses with fewer subjects. Moreover, the robust effect sizes found here with multiple measures of holistic processing confirm the hypothesized link between the ability to perceive the interdependence among facial components and face recognition ability. This re-affirms the holistic processing/face recognition connection that is tacitly assumed by studies of the development of face processing (Cashon, 2003), prosopagnosia (Busigny et al., 2010; Ramon et al., 2011), the other-race effect (Michel et al., 2006; Rhodes et al., 1989), and computer models of face processing (Cottrell, Dailey, Padgett, & Adolphs, 2001).

Having provided evidence for a unitary holistic face processing construct and the fundamental connection between holistic face processing and face recognition ability, the foundation is now laid for further examinations of this connection. One possibility is that greater holistic face processing ability allows one to more efficiently build and store a more distinctive face representation in long-term memory, leading to better face recognition performance. Evidence supporting this possibility is from the current PW results, which in addition to having a large perceptual component, also requires visual short-term memory (VSTM). From a VSTM perspective, the significant relationship of PW with CFMT could indicate that those who build a more holistic face representation in VSTM (or do so more rapidly) have better general face memory abilities. Providing additional evidence for this notion, Curby and colleagues (2007) found significantly greater VSTM capacity for upright faces and objects of expertise than for inverted faces or cars, suggesting that the more holistically an object is processed the more efficiently and richly coded it is in VSTM. Recent evidence also suggests that the distinctiveness of face representations in long-term memory, as can be measured by the strength of face-specific adaptation effects, is predictive of face recognition ability (Dennet, McKone, Edwards, & Susilo, 2011). It would be informative to test if holistic perceptual processing abilities correlate with these face-specific adaptation effects and if so, whether holistic processing mediates the relationship of face-specific adaptation with face recognition ability.

Though the main focus of this study was holistic face processing and its connection to face recognition ability, we also found that non-holistic processing is an important aspect of face recognition ability. For both PW and CT, part trial and misaligned trial performance explained a significant amount of CFMT variance above and beyond holistic processing. This is counter to Richler et al. (2011a) who found, when predicting CFMT scores from their CT task, that misaligned trials had no significant predictive ability beyond holistic processing. The origin of this differing result is unclear. Our findings do, however, replicate across both PW and CT, and they also converge with other recent studies supporting the importance of non-holistic processing to face recognition ability. For example, prosopagnosics have a deficit in discriminating face parts, particularly when judging shapes of facial features (Le Grand et al., 2006; Yovel & Duchaine, 2006). Additionally, the own-race face recognition advantage is significantly related to how much better subjects are at remembering own-race facial features (Hayward, Rhodes, & Schwaninger, 2008). While our results clearly suggest that holistic face processing is a key mechanism involved in skilled face recognition, they also leave room for important contributions from non-holistic face processing and/or non-face processing mechanisms.

5. Conclusion

Using a regression-based approach, we validate the construct of holistic face processing by demonstrating that part-whole and composite task holistic processing measures correlate with each other. Additionally, using this approach we provide strong converging evidence of the link between holistic processing and face recognition ability, as individually both part-whole and composite measures showed robust correlations with face recognition ability. Finally, we provide evidence that non-holistic factors also strongly correlate with face recognition ability. Together, these results put the link between holistic face processing and face recognition on firm ground and more broadly illustrate the utility of a regression-based approach for associating and dissociating individual differences in human cognition.

Contributions

JD performed data analysis, wrote the manuscript, and contributed funding. JW conceptualized and oversaw all aspects of data analysis and contributed to manuscript preparation. RM recruited and tested subjects, performed data analysis, and contributed to manuscript preparation. SC performed data analysis and contributed to manuscript preparation.

Acknowledgements

This work was supported by a Veterans Affairs Career Development Award II granted to JD.

Appendix A. Supplementary Materials

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2012.09.004.

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