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The relationship between baseline EEG spectra power and memory performance in older African Americans endorsing cognitive concerns in a community setting

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Abstract

The finding that some older individuals report declines in aspects of cognitive functioning is becoming a frequently used criteria to identify elderly at risk for mild cognitive impairment (MCI) and dementia. Once concerns are identified in a community setting, however, effective means are necessary to pinpoint those individuals who should go on to more complex and costly diagnostic evaluations (e.g., functional imaging). We tested 44 African American volunteers endorsing cognitive concerns (37 females, 7 males) age 65 years with CogState battery subtests and recorded resting-state EEG, with eyes closed. After current source density (CSD) transformations of EEG recordings we obtained spectral power for delta, theta, alpha, and beta frequency bands. We characterized CogState One Card Back (ONB, working memory) and One Card Learning (OCL, memory) with diffusion model parameters drift rate, boundary and non-decision time (NDT). Forward regression models showed that lower OCL drift rate, slower accumulation of information needed for decision making was linked to increased absolute and relative delta at occipital region. Lower drift rate was also linked to decrease in OCL theta power at parietal region, with no findings for ONB. Results show that cortical resting, eyes closed EEG rhythms are related to memory in African American seniors endorsing cognitive concerns. This study further supports the use of EEG as an easily accessible, cost-effective, culture-fair, and noninvasive clinical measurement that could provide potentially reliable diagnostic (and perhaps prognostic) information to differentiate at-risk from stable African American seniors.

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Keywords

African Americans; recognition memory; diffusion model; resting-state EEG; delta; theta

Introduction

In the context of the rapid increase in longevity and considerable expansion of the share of elderly in the general population, ubiquitous age- and disease-related cognitive declines have important socioeconomic implications. Thus, identifying those who are at risk for mild cognitive impairment (MCI) and understanding mechanisms leading to these declines are vital for guiding environmental and clinical interventions aimed at cognitive rehabilitation of older adults and early prediction of dementia. Health disparities, however, represent a critical roadblock to early identification of MCI and mitigate the dramatic social, economic, and fiscal benefit that slowing cognitive decline and dementia progression brings, not only to the individual patient and family, but also on the state and federal level. Overall, community dwelling African American seniors access diagnostic services later in their illness and are underrepresented in dementia drug trials. Development of culturally acceptable, reasonable, cost effective, and economically viable methods of early detection of older persons with MCI from underserved populations who are at risk for dementia are thus critical. Also critical is the ability to adapt specialized assessment approaches to a community-based setting, wherein a wider range of participants can be screened effectively, benefitting both early clinical evaluation and outreach for clinical trials in the African American population.

Portable electrophysiological measures (i.e., electroencephalography, EEG, or evoked potentials, ERPs) represent a unique approach for developing community-based outreach that can facilitate very early, enhanced, neurophysiological-based diagnostic accuracy. EEG represents an objective, easily accessible, cost-effective, culture-fair, noninvasive evaluation method. This methodology can detect subtle functional changes that could be used to predict neuro insufficiencies related to cognitive decline in healthy elderly.

This paper presents data from a community- based study of recorded EEG compared to memory performance in a sample of older African American volunteers. Older African Americans were selected on the basis of self-reported change in some cognitive ability over the last year (subjective memory concerns/complaints, SMC), in order to enhance the potential range of memory performance and better evaluate the relationship between baseline, resting-state EEG signal and memory performance.

Resting-state EEG

Brain neuroelectric oscillatory activity is a hallmark of neuronal network function in various brain regions. Modern neurophysiological techniques, including EEG, can accurately index normal and abnormal brain aging to facilitate non-invasive analysis of cortico-cortical connectivity, neuronal synchronization of firing, and coherence of rhythmic oscillations at various frequencies. The brain's spontaneous, intrinsic activity is increasingly being shown to reveal brain function and assist in diagnosing brain disorders.

Brain neuroelectric signals during the so-called ‘resting state’ (when participants are requested to rest, with eyes closed or eyes open, and without ongoing physical or mental activity), represent intrinsic neural activity. Better understanding of underlying brain coupling dynamics can potentially provide significant insights into the aging process, as well as cognitive decline from neurodegeneration. Numerous studies have explored the association between various EEG cortical frequency bands of delta (1–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–28 Hz), and gamma (>30 Hz) oscillations in association with different behavioral and disease states.

Age-related cognitive decline can be in part characterized by the progressive loss of functional connectivity within cortical areas resulting in dedifferentiation and reduced cortical activity (Baltes & Lindenberger, 1997; Li, Lindenberger & Sikstrom, 2001; Park, Carp, Hebrank, Park & Polk, 2010; Reuter-Lorenz & Park, 2010). EEG provides a tool to investigate these early alterations of neural networks, providing a potential biomarker for various neurological and psychiatric disorders (Fox and Greicius, 2010). In this way, EEG could provide an early predictive model of MCI development among elderly with progressive cognitive decline.

Several EEG research groups have shown that resting state, gradual modifications in the spectral power profile, so called global “slowing” of the intrinsic EEG, occurs with aging. This is reflected by pronounced increases in power in the slower delta (2–4 Hz) and theta (4–8 Hz) frequency ranges localized at centro-temporal and parieto-occipital sites (for review see Klass and Brenner, 1995; Klimesch, 1999; Rossini et al., 2007) and decrease of alpha (8–13 Hz) rhythm (Babiloni et al, 2006; Muller and Lindenberger, 2012; Reichert et al 2016). In contrast to the findings above with delta activity, a study by Widagdo et al., (1996) did not find differences in resting delta activity. In support of Widagdo study (1996) several additional research groups have reported decreased delta activity in older, as compared to younger, participants (Cummins and Finnigan 2007; Leirer et al., 2011; Reichert et al 2016; Vlahou et al., 2014).

Further, “slowing” of EEG has been reported as healthy older individuals progress to MCI and probable Alzheimer's disease (AD) (for review see Vecchio et al., 2013). AD patients, as compared to healthy older adults, demonstrate further increased power in delta and theta rhythms and decrease power in posterior alpha (8–12 Hz) and beta (12–30 Hz) frequency (Babiloni et al., 2011, Babiloni et al., 2014; Baker et al., 2008; Jeong, 2004; Prichep, 2005). Research in resting state EEG with MCI patients, the prodromal stage of AD, has shown intermediate EEG changes, as compared to healthy older adults and diagnosed AD patients. Specifically, intermediate increase in power of delta and theta frequency (Kwak, 2006) and intermediate decrease in alpha rhythms in the parietal and occipital regions (Coben et al., 1985; Babiloni et al., 2006; Luckhaus et al., 2008; Moretti et al., 2011) has been found.

Few studies have investigated the ability of resting state EEG to predict the conversion from MCI to AD (Antila et al., 2013; Jelic et al., 2000; Poil et al., 2013; Prichep, 2005). In two studies, the EEG markers of MCI to AD progression included a power increase of theta rhythms in temporal and occipital regions, as well as a power decrease of beta rhythms in the temporal and occipital regions (Jelic et al., 2000; Poil et al., 2013). Prichep et al. (2006)

reported that when seniors with SMC were followed for up to nine years, there was a significant increase in theta power among those who converted to MCI. On the other hand, Poil et al. (2013) showed that following 86 patients initially diagnosed with MCI for two years, during which 25 patients converted to AD, mainly changes in the power in beta-frequency range (13–30 Hz) predicted conversion from MCI to AD.

Age-related resting EEG spectral changes in theta (approx. 4–8 Hz) and alpha (approx. 8–12 Hz) frequencies also have been linked to age-related memory declines, though reports have not always been consistent. For example, Klimesch (1999) reported that older adults with lower resting state theta rhythms performed better on memory tests than those with higher rhythms. In contrast, Finnigan and Robertson (2011) found that those with higher resting-state theta power actually performed better with cognitive performance (i.e., immediate and delayed recall, executive function, attention). Reports about the relationship between alpha power and cognition are consistently showing that higher resting-state alpha power is associated with better performance in memory tasks (Klimesch et al., 1999; Lopez Zunini et al., 2013; Vogt et al., 1998). More recently, Reichart et al. (2016) reported that subjects in eyes-open state with higher theta power at fronto-central locations perform better on verbal memory test while subjects with higher alpha II (10–12 Hz) power in eyes-closed state at parietal locations performed better on visuospatial memory test.

Diffusion model

Relationships between brain activity and memory recognition processes have been historically based on separate analyses of response latencies and/or accuracy measures. The Diffusion Model approach for analyzing recognition data, however, represents a new approach, combining both response time and accuracy to provide additional insight into information processing. According to the diffusion model, following stimulus onset in a two-alternative, forced-choice memory recognition task (e.g., new-old), as used in this study, the decision process can be characterized by initially random, noisy processing moving toward one of 2 decision boundaries (i.e., “new” or “old” recognition response; Figure 1). Evidence for one of these two possible responses randomly varies until the person starts to accumulate information toward one decision or the “boundary”. This process is labeled “drift rate” (i.e., the rate at which information is accumulated). Once this accumulation process passes a boundary for one of the possible responses, that response is initiated. Performance is, therefore, a function of the rate of information accumulation (*drift rate*), the distance to the boundary for the correct response from the starting location of the diffusion process (*boundary separation*), and the perceptual and response factors that are combined in the model into what is labelled as non-decision time (*NDT*). Drift rate indicates the speed and quality of information buildup toward the correct response, while boundary reflects response caution or the amount of evidence a person needs before executing the response.

The diffusion model has been applied to differentiating persons at risk for cognitive impairment from healthy controls. Aschenbrenner et al. (2016) reported that individuals with a family history of AD exhibited lower recognition accuracy, represented in the diffusion model as decreased drift rate that could not be explained by APOE status, differences in

response caution, or other diffusion model parameters. These authors suggested that drift rate could be considered as a novel cognitive marker of preclinical AD.

In summary, it is hypothesized that spontaneous brain activity measured at rest may provide information about normal and/or pathological aging processes and may predict the level of proficiency in explicit cognitive tasks using more sophisticated measures of memory performance. The aim of the present study was to investigate the degree to which spectral power of resting-state EEG frequencies relate to memory performance in older, non-demented African Americans who have been identified as endorsing subjective memory concerns, and to compete these examinations within the community setting as compared to a laboratory environment. This exploratory study examined: 1/ whether the acquisition of EEG in the community setting is feasible, 2) whether such EEG acquisition methods provide reliable signals, and 3) if resting-state EEG is sensitive to memory performance as evaluated the diffusion model parameters. Based on above reviewed findings, we anticipated that increased power in lower frequencies (slow wave excess) would be linked to decreased performance on a computerized measure of memory (CogState One Card Learning, OCL). We also used a CogState working memory subtest (One Card Back, ONB) to evaluate the specificity of the EEG measures for memory performance.

1. Methods

1.1 Subjects

We recruited 44 African American participants (37 females, 7 males) age 65 years and older (mean = 74 years, range = 65 to 87 years) from the greater Detroit area. Some of the participants were recruited out of the pool of over 1125 registered volunteers in the Healthier Black Elders Center (HBEC), a joint collaboration between Wayne State University's (WSU) Institute of Gerontology and University of Michigan's Institute of Social Research (Chadiha et al., 2011) and others were recruited through the Michigan Alzheimer's Disease Center (MADC) from outreach programs in local churches and community centers. Participants were enrolled based on their responses to a question included in the health screening forms asking if they had experienced a change in memory or other cognitive areas over the past year, but not so severe as to interfere with their ability to complete daily activities. All participants underwent the National Alzheimer's Disease Cooperating Centers (NACC) standardized assessment battery, including medical, neurological, and neuropsychological assessments. Consensus conferences (including neurologists, nurses, technicians, and neuropsychologists) were then initiated for all participants, without discussion of the EEG and CogState results. Diagnoses were determined after excluding other medical conditions (e.g., psychiatric conditions, serious sleep problems) as possibly contributing to any evident cognitive issues. Other specific exclusions included evidence of head injury with loss of consciousness for longer than 30 minutes, the history of a seizure disorder, mental retardation, AIDS, radiation therapy to the brain in the past year, history of alcoholism and/or drug abuse, and major medical illnesses, such as cancer, in the last 5 years. Any potential participants with a diagnosis of dementia or with medical issues that were judged to possibly affect cognitive ability or unduly affect study procedures were excluded from the current study. Accordingly, all the participants included in this study were

deemed as to be non-demented based on their MMSE scores 25 and lack of symptoms suggesting interference with everyday functioning. All participants were consented and procedures were approved by the Wayne State University Research Subjects Review Board and the University of Michigan Medical School Review Board (IRB MED).

1.2 EEG Recordings

Scalp electroencephalographic (EEG) activity was recorded using Brain Vision (Brain Vision, Inc.) equipment. We used the high density Acti Cap (64 active electrodes) modified according to the International 10–20 System. The recording locations included eight midline sites, with the FCz electrode as an on-line reference and a ground at midline location AFz. Low and high pass filter settings were 70 Hz and 0.1 Hz, respectively. The cutoff frequencies for these filters were set at 3 dB down; the roll off was 12 dB per octave at both sides. Impedances were maintained below 10 k Ω for each channel and balanced across all channels within a 5 k Ω range. The sampling rate was 500 Hz with 32 bit resolution.

1.3 Baseline Recordings

After having the electrode cap with 64 electrodes placed and satisfactory impedances obtained, the participant was seated in a comfortable chair, adjusted for height, in a dimmed lit room. EEG was recorded for 3 minutes of resting-state with eyes open and 3 minutes with eyes closed. We opted for presenting spectral analyses obtained only with eye-closed baseline EEG recordings, because we wanted to be as close as possible to the true baseline (Duncan et al 2013). Specifically, it has been documented that resting state with eyes open engages functioning in the visual system (presumably activating widespread communication of cortical and thalamo-cortical interactions) that activate the entire cortex to aid information processing and thus affect EEG spectral profile during eyes open. Barry et al. (2007) showed that during the eyes-open, as compared to eyes-closed, mean activity in the delta, theta, alpha, and beta bands are reduced across-sites.

1.4 CogState Testing

A standardized computerized neuropsychological screening battery, CogState, was used to assess specific aspects of cognitive functioning. This brief computerized battery is comprised of interchangeable tasks covering several cognitive domains. For all tests, the stimuli consist of playing cards that lessen the test's dependence on specific languages and/or culture factors due to the universal familiarity of playing cards that also ensures the tasks are inherently interesting. CogState has been demonstrated to be reliable and stable and resistive to practice effects (Darby et al., 2002; Fredrickson et al., 2010) and sensitive to both MCI (Darby 2011; Hammers et al., 2011) and early cognitive changes in healthy controls (Darby et al., 2002; Darby et al., 2012). Two subtests were chosen for this study. The One Back Working Memory (ONB) subtest, a measure of working memory, asks the participant to watch the computer screen to view a series of single card presented centrally and then respond "YES" if each presented card is the same as the previous card or "NO" if it is different. The One Card Learning [OCL] test is a visual episodic recognition memory task that requires the participant to decide whether a single centrally presented card on the computer screen was or was not presented previously. Specific log-transformed primary and secondary measures are available for each task based on response times and accuracy (c.f.,

Hammers et al., 2011). Accuracy scores from OCL and ONB were used for outcome measures, while response times, variability of responses times and accuracy on OCL subtest were used to evaluate EZ diffusion model parameters.

1.5 Experimental procedures

The computerized testing and EEG recordings were performed in a community center, the University of Michigan (UM) Detroit Center. To obtain acceptable EEG signal, several available spaces were evaluated with a Gauss meter prior to EEG recording to find the area with the least external noise (preferably < 3 mG). Active electrodes also were used to isolate external noise, to minimize cable movement, motion artefacts, and to keep impedances at bellow $10\text{k}\Omega$ (Kappenman et al., 2010).

All subjects underwent computerized testing and EEG recordings in a single session, spaced apart by at least half an hour. Upon signing the consent forms, the majority of the subjects initially underwent computerized testing followed by EEG Recordings. We opted for computerized testing first, followed with EEG recordings, because we wanted to facilitate participants being able to return home to remove any possible residue of electrogel.

1.6 EEG Data Analyses

We used off-line inspection to identify and remove segments of EEG contaminating either excessive noise, saturation, or lack of EEG activity. The EEG data were then segmented in consecutive epochs of 2 seconds and were analyzed off-line (1024 data points; 0.488 Hz resolution; Hanning window). The epochs were identified as acceptable by an automatic computerized procedure using a rejection criterion of 100 mV on any channel affected by artifacts (muscular, instrumental). Per subject we obtained 90 (range, 64–115) 2 seconds artifact-free segments to perform FTT analyses to evaluate power in major frequency bands: delta (2–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and beta (12–30 Hz). We did not include in power analyses frequencies > 30 Hz due to pericranial musculature electrical activity that can contaminate scalp recorded neuroelectric activity (Whitham, 2007). A total of six regions of interest (ROIs) were selected for further analysis (Fig. 2): frontal – F (Fp1, Fp2, AF3, AF7, AF4, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8, Fc5, FC3, FC1, FC2, FC4, FC6), Left temporal - LT (FT9, FT7, T7, TP7, TP9) and Right temporal - RT (FT10, FT8, T8, TP8, TP10), central - C (C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6), parietal - P (P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, POz, PO4, PO8), and occipital - Occ (PO9, O1, Oz, O2, PO10).

Prior to FFT, EEG epochs were transformed into the reference-free current source density (CSD) distribution, which reflects the underlying cortical activity and removes nearly all volume conduction effects (Keyser & Tenke, 2015a, 2015b). Topographic distribution of power was obtained to compute grand-average power across subjects for assessing associations between EEG rhythms power in different ROIs and cognitive performance on different cognitive domains.

Initially, we computed absolute power for each ROI by averaging across electrodes within the ROI (Fig. 2). We also calculated individual alpha frequency (IAF) peaks, defined as the frequency of the strongest EEG power at the extended alpha range (Klimesch, 1999).

Subsequently, we calculated delta and theta relative power (absolute delta, theta power as a percentage of total power). We used the following EEG parameters for the analyses: 1) absolute power in all above frequency bands, 2) delta and theta relative power, 3) individual alpha peak frequency, and 4) individual alpha peak power.

1.7 EZ-diffusion model

For evaluation of diffusion model parameters we used the EZ diffusion model (Wagenmakers et al., 2007), a recent simplification of the diffusion model of Ratcliff (1978). The parameters of the EZ-diffusion model (boundary, drift rate and non-decision time) were calculated for the OCL subtest using response times and variances to correct trials and accuracy (proportion correct). A more detailed description and the formulas of the EZ-diffusion model is available in Martin et al. (2010).

1.8 Statistical procedures

SPSS for Windows (release 22.0.0) was used for data analyses. Initially, all the measures were evaluated for normality using Shapiro-Wilk's test. As expected, all the EEG spectral power measures violated normality. To achieve normal distribution, logarithmic transformation was used. We used forward regression to identify EEG power variables that are related to the performance on the two CogState subtests. In forward regression, the variable with the strongest relationship to the criterion variable is entered first, and then the variable with the strongest relationship to the residuals is entered next, and so on. Entry stops when no variable among the candidate predictors changes the coefficient of determination (R^2) significantly. To be conservative, considering the number of sets of calculations, we only considered predictors at the $p < .01$ or better level.

2 Results

2.1 Memory performance

Results show that participants' basic accuracy scores on the CogState recognition memory subtest, OCL, and on the working memory subtest, ONB, were generally within the average range as compared to CogState normative data (CogState Normative Data, www.cogstate.com, info@cogstate.com). OCL accuracy for the entire sample was on average 0.93 (0.10), below normative data 1.00 (0.10), and varied from at chance level – 0.71 to as high as 1.13 (Figure 4, panel B). ONB accuracy was accuracy 1.30 (0.18), almost identical to normative data 1.31 (0.10).

2.2 Aging effects

We correlated age with the CogState accuracy and diffusion model parameters (i.e., drift rate, boundary, and non-decision time) and EEG spectral powers. For the EEG spectral powers, statistically significant positive correlation were found between age and normalized delta power at left temporal and parietal ROIs ($r = .39$, $p = .008$; $r = .36$, $p = .02$, respectively) and theta power at the left temporal ROI ($r = .29$, $p = .05$). There were no significant correlations between age and any of the CogState scores.

2.3 Baseline EEG spectral analyses

As expected, topographical figures of spectral power from the eyes-closed resting-state EEG for older African Americans (Figure 3, upper panel) showed the highest delta power at frontal region, highest theta at fronto-central region, highest alpha at parieto-occipital region, and highest beta at frontal, temporal and occipital regions. Also, as expected, there was considerable peak alpha power in posterior regions (Figure 3, lower panel).

2.4 Forward Regressions analyses

Parameter estimates from the forward regressions are given in (Table 1). The forward models showed that several independent variables from absolute power, relative power and peak alpha power predicted performance on OCL subtest as evaluated by diffusion model parameters. There were no significant relationships for the ONB scores.

2.5 Absolute power

Forward regression showed that the 2 independent variables, delta power at occipital ROI ($\beta = -.67$) and theta power at parietal ROI ($\beta = .37$), significantly predict drift rate on OCL subtest ($R^2 = .23$) (Figure 4). Results show the high drift rate is correlated with low delta power at occipital ROI and high theta power at parietal ROI.

2.6 Relative power

The forward regression model for relative power is similar to that with absolute power: drift rate for OCL was significantly predicted by relative delta power at the occipital ROI ($R^2 = .20$, $\beta = -.47$) (Table 1).

2.7 Peak alpha

Consistent with average alpha power, forward regressions did not show significant predictions with peak alpha amplitudes nor latency.

Overall, better performance on the OCL subtest (high drift rate) is related to the low delta at occipital ROI and high theta power at parietal ROI.

3. Discussion

The current study examined in a community setting the relationship between the working memory (ONB) and recognition memory (OCL) subtests from the CogState battery with EEG power registered during eyes closed, resting-state in African American seniors with subjective cognitive concerns. We observed significant links between different measures of EEG spectral power and performance on recognition memory (OCL), but not working memory (ONB) CogState subtests. The performance on OCL was modeled by diffusion model parameters where better performance is reflected by higher drift rate reflecting the faster rate of accumulation of information towards the decision making process and lower boundary parameter, a reflection of the length of time someone needs to reach a decision. Overall, we observed that lower OCL performance was significantly negatively correlated with slowing of the resting EEG, as reflected in higher absolute and relative delta power and lower theta power. Specifically, lower OCL drift rate (slower decision making processing)

was linked to increased absolute and relative delta at occipital ROI and decrease theta power at parietal ROI. No significant relationship was found between resting EEG spectral power and scores on ONB task, suggesting these relationships are specific for memory and not associated with attention or working memory. In addition, we found significant correlations between age of our participants and their baseline EEG spectral powers: there was significant positive correlation between the age and normalized delta power at left temporal and parietal ROIs and normalized theta power at the left temporal and parietal ROIs and normalized theta power the left temporal ROI. Somewhat unexpectedly, we did not find any significant correlations between the age of African American participants with subjective cognitive concerns and their performance on OCL and ONB subtest.

3.1. Relationship between resting-state EEG power and memory performance

Few studies have investigated relationships between EEG spectral power and cognitive performance in healthy, older participants. The present results extend the previous EEG evidence showing that increased power in delta frequency bands are correlated with decreased memory performance in non-demented older participants (Hartikainen et al. 1992). Our findings confirm earlier reports showing that increased delta spectral power was predictive of decreased memory but not working memory performance are somewhat different from earlier report showing that increased resting state delta activity is significantly negatively correlated with performance on working memory (Roca-Stappung et al. 2012). This difference could be explained in part that we used more basic, less demanding measure of working memory, while Roca-Stappung et al. (2012) used a composite score based on more complex tasks (eg., mental arithmetic, letter-number sequencing). Our findings of positive link between theta power and memory performance on OCL are in partial agreement with Finnigan and Robertson (2011) who showed that elderly with higher resting-state theta power performed better on cognitive tests (i.e., immediate and delayed recall, executive function, attention).

The functional meaning of resting-state EEG rhythms is not yet well understood. It can be speculated that the association between higher power in lower rhythms oscillations and cognitive performance might be related to loss of hippocampal and posterior cortical neurons, which are affected by cholinergic inputs. Indeed, it has been demonstrated that functional connectivity between the hippocampal formation and temporo-parietal cortex can be affected by early degeneration in the mesial temporal cortex of MCI and AD subjects (Killiany et al., 1993). Furthermore, in AD patients, an increase of delta rhythms in the posterior cortex is correlated with a reduction of gray matter volume in the hippocampal formation and entorhinal cortex of AD subjects (Fernandez et al., 2003). In addition, previous studies have shown that resting rhythms were lowered by experimental damage to the cholinergic pathways, consistent with a possible relationship to the development of cholinergic-related diseases, such as Alzheimer's dementia (Holschneider et al., 1998; Mesulam, 2004).

One of the fundamental characteristics of the brain is its continuous oscillatory activity and ability to generate rhythmic potentials. The brain is structurally organized into dynamic functional networks that can be transiently connected and/or independent. The nature of

connectedness/independence dynamics is not yet well understood. According to Pfurtscheller (2003) such a network can be controlled by the thalamo-cortical feedback loop or by intracortical feedback loops (e.g., interneurons). Alpha band rhythms are hallmarks of thalamo-cortical activity, which presumably modulate local cortical activity (Doesburg et al., 2012). Previous findings suggested that alpha rhythms are one of the physiological mechanisms by which the frontal associative cortex modulates the efficiency of information processing in posterior cortical areas as a function of attentional top-down processes (Engel et al., 2001; Sauseng et al., 2005). Our findings are in line with this proposed mechanism, since our results indicate that there must be some relationship (e.g., overlap or connectedness) between resting-state, default neuronal networks and subsequent engagement of those neuronal networks needed for recognition memory processing. In other words, effective cognitive processing depends on the selectivity and flexibility of the excitation and inhibition across brain neural networks during the resting state condition and task demands (see for example the concept of effective functional connectivity; Friston, 2011; Kundu et al., 2013). These relationships appear specific for learning and memory functions, as the ONB subtest involving working memory and concentration did not reflect correlations with EEG spectral power measures.

Results of this study demonstrate that resting-state, baseline EEG recordings represent simple, cheap, non-invasive, and acceptable means of measuring and recording neurophysiological functioning in a community-based setting. As this work continues, it should lead to better understanding of the extent to which baseline EEG recordings can identify older participants at risk for cognitive decline and even, perhaps, predict which of those participants are more likely to progress to MCI and AD.

3.2. Diffusion model

Use of the diffusion model parameters is a methodology for interpretation of cognitive test information that is not commonly used in clinical settings and is yet to be used routinely for research. However, previous research does suggest, as supported by our findings, that it can be used to reliably characterize decision processes and differentiate decision from non-decision time in cognitive processing. Using this model, Ratcliff and colleagues (Ratcliff et al., 2003; 2006) found that older subjects accumulated information and adopted a response threshold similar to that of younger subjects. We have previously reported similar findings with a visual motion direction discrimination task in older adults, in which we demonstrated increased non-decision time for older participants and that diffusion model parameters (i.e., drift rate, boundary, and NDT) were significantly correlated with stimulus onset visual evoked potentials (VEPs) (Kavcic et al. 2013). Thus, older participants had longer NDT, indicating that the slowing was specific to perceptual or response processes, rather than a global cognitive slowing. Ratcliff et al. (2006a) also found evidence of a more conservative threshold among elderly participants, in addition to greater NDT, though a relationship between age and drift rate was not evident. However, Thapar et al. (2003) found that older participants had longer NDTs, more conservative thresholds, and slower drift rates. Thapar's findings were supported by latest study by Aschenbrenner et al. (2016), who found that in older adults with history of AD, lower memory recognition accuracy was correlated with slower drift rate

Our findings of significant negative correlations between decreased diffusion model parameters for recognition memory performance and increased EEG power in delta and theta are comparable to those of Thapar et al. (2003) and Aschenbrenner et al. (2016), who reported slower drift rates in older participants. In the current study, correlations between decreased drift rate with increased power in delta rhythms and decreased power in theta rhythms further clarify behavioral findings, by showing that in elderly African Americans with memory concerns, it is the decision processing and not perceptual/motor processing, which correlate with “slowing” of the EEG.

3.3. Aging effects

We found significant correlations between age and EEG power in lower frequency bands, with normalized delta and theta power increasing with older age. Robust age-related increases in oscillations have been reported by other groups for delta (approx. 2–4Hz) and in the theta (approx. 4–8 Hz), reflecting the “slowing” effect of age on EEG (Klimesch et al., 1999; Rossini et al., 2007). Our findings are in line with these previous studies with respect to delta power (Babiloni et al. 2010) and theta power (Alexander et al., 2000; Klimesch et al., 1999). As noted earlier, an increase of power in slower frequencies (i.e., delta and theta) can be regarded as a marker of pathological aging (Klimesch, 1999). In the present study, “slowing” of EEG is to be expected, given the overall age of this sample of older non-demented African Americans who expressed cognitive concerns. It is possible that those with the greatest relative slowing of EEG are on a trajectory for increased cognitive difficulties and possibly dementia as they age, though only a longitudinal study would provide evidence of the prognostic relevance of this finding.

It is interesting to note, however, that although correlations were found between age and some of the EEG measures, no correlations between age and performance were evident on the OCL and ONB scores. We believe that the limited age range in our sample (65 to 87 years of age) and the smaller sample size most likely reduced the opportunity of seeing a relationship between age and the cognitive measures. This finding essentially highlights the increased sensitivity of the electrophysiological measures to aging.

3.4. Strengths and limitations

A strength of the current study is that for the first time in a community-based setting, EEG recording in a sample of older African Americans with cognitive concerns was able to demonstrate significant relationships between cortical rhythms and mnemonic processing. This relationship was specific to recognition learning and not to measures of working memory. We were thus able to show the feasibility and specificity of such a biological marker in a community setting and to show that participants would be overwhelmingly willing to undergo EEG recording. Our results also suggest that this approach may be useful in identifying individuals in need of further monitoring through more involved and/or invasive medical center-based measures. EEG-based markers within a community setting also may be quite helpful in clinical trials by identifying persons most at-risk for early cognitive decline, as well as for tracking changes in neural functioning in response to pharmacological or nonpharmacological interventions. There are some limitations to be considered in this study. The main limitation is the relatively small sample size, though the

uniqueness of a community sample of African Americans must be considered. A replication in a larger sample and within a more gender- balanced participant pool is currently underway.

4. Conclusions

The results of the present study showed that resting-state cortical EEG rhythms are specifically related to memory functioning in a sample of community-dwelling older African Americans. The present results support future studies on the predictive value of cortical EEG rhythms in the early identification of those elderly who may be at risk for memory problems and who might go on to convert to MCI and potentially dementia. Ideally, such a discrimination of converters from non-converters would best be addressed through longitudinal cohort. In addition, changes in EEG rhythms could be potentially valuable for evaluating the efficacy of pharmaceutical and cognitive enhancement therapies for prevention of pathological aging.

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Figure 1.

Schematic illustration of the diffusion model decision process. A person starts to accumulate information from a starting point at Z, and a response begins to drift towards a decision boundary either toward the correct response (Category a – “new”) or the incorrect response (Category b – “old”) with some degree of random fluctuation. The decision time is the time to reach the boundary. The decision time is determined by how quickly information accumulates (drift rate v) and how much information must accumulate before the person initiates a response (boundary separation). That is, the higher drift rates and the boundaries closer together the faster decision time.

Figure 2.

The 62 EEG recording sites and the demarcation of the six ROIs: red marked electrodes represent frontal ROI, green marked electrodes represent left and right temporal ROI, dark blue marked electrodes represent central ROI, light blue marked electrodes represent parietal ROI, and purple electrodes represent occipital ROI.

Figure 3.

Topographic plots for delta, theta, alpha, and beta power (top panel) and spectral power plot for all vertex electrodes (lower panel).

Figure 4.
Correlation between obtained and predicted drift rate (DR) by delta power at occipital ROI
and theta power at parietal ROI

Table 1:

Significant findings for forward regression analyses predicting diffusion model parameters from baseline EEG spectral power

Condition	Criterion	Predictor(s)	F	df	p	β	AdjR ²	S _{Y X}
Abs. power	Drift rate	Delta Occ ROI	9.65	(1,43)	.003	-.67	.23	.03
		Theta Par ROI				.37		
Rel. power	Drift rate	Delta Occ	11.85	(1,43)	.001	-.47	.20	.03

Note: β = standardized regression weight; Adj R² = adjusted R²; S_{Y|X} = standard error of estimate