Serial order and consonant–vowel structure in a graphemic output buffer model

David W. Glasspool a,*, George Houghton b

a Department of Psychology, University College London and Institute of Cognitive Neuroscience, University College London, UK
b School of Psychology, University of Wales, Bangor, UK

Accepted 14 January 2005
Available online 25 February 2005

Abstract

We review features of the spelling errors of dysgraphic patients with “Graphemic Buffer Disorder” (GBD). We argue that the errors made by such patients suggest the breakdown of a system used to generate serial order in the output stages of spelling production, and we develop a model for this system based on an existing theory of sequential behaviour—“Competitive Queuing.” We show that constraints on response categories may be straightforwardly applied during sequence production in such a model, and this enables us to account for the preservation of consonant–vowel status in the spelling errors of GBD patients. When the sequence generation process is disrupted by the addition of random noise the model shows the major features of GBD. The results are compared in detail against data from a number of patients.

Keywords: Graphemic buffer; Spelling; Serial order

1. Introduction

The problem of the processing of written language has long interested cognitive, developmental, and neuropsychologists. Particular attention has been paid to the “input” side of the problem—reading—and this has led to the development of a number of computational models, most employing connectionist formalisms, e.g., Grainger and Jacobs (1996), Norris (1994), Plaut, McClelland, Seidenberg, and Patterson (1996), Zorzi, Houghton, and Butterworth (1998) (see also Coltheart & Rastle, 1994, for a “hybrid” connectionist/symbolic model). The “output” aspect of written language, in particular spelling, has also been the focus of substantial empirical and theoretical research. Spelling is to some extent the inverse process to reading. Whereas in reading, familiar letter strings access semantics and phonology, in lexical spelling semantic and phonological inputs can retrieve a memorised sequence of letters. Reading by spelling-sound conversion has its approximate inverse in sound-spelling conversion (phonological spelling).

However, a major difference between word reading and spelling is that reading of individual words appears to involve a large degree of parallel processing of the input, particularly for shorter strings and for known words. This parallelism is easily handled by standard neural network architectures as in the models cited above. Spelling however requires the endogenous generation of serial behaviour: letters are produced one at a time, and must be produced in the correct order. Current computational models of sound-spelling translation typically only go as far as activating a set of letter or grapheme nodes in parallel, without specifying how this spelling “plan” is read out (e.g., Houghton & Zorzi, 2003). In this paper, we argue that a full understanding of spelling, and in particular an understanding of disorders and deficits in spelling ability, must include detailed
consideration of the psychological mechanisms underlying the representation and control of serial order in behaviour. We develop a model for the serial production of letters (an example of a more general class of models) and test it in detail against error data from a group of patients exhibiting “graphemic buffer disorder” (Caramazza, Miceli, Villa, & Romani, 1987). Before describing the model we first review the major features of this disorder, and then relate these to a general theoretical framework for the generation of serial order.

2. Graphemic buffer disorder

Graphemic Buffer Disorder (GBD) is an acquired disorder of spelling (agraphia). The term derives from “dual route” models of spelling (e.g., Morton, 1980; Seymour & Porpodas, 1980). On such models, the so-called graphemic buffer receives input from two sources—A graphemic output lexicon, providing learned spellings for familiar words, and a phonology-to-orthography mapping system, allowing spelling from phonology by means of sound-to-spelling conversion. The graphemic buffer is assumed to store the final spellings of letters (an example of a more general class of models) from which a representation of the spelling is assembled for serial output. While studies of different patients vary greatly in the level of detail available the spelling errors made by GBD patients do show a distinctive pattern which is not predictable from the basic spelling model, the consistent features of which are as follows:

2.1. Effect of word length

Accuracy of spelling in GBD declines with increasing word length. The effect is reported for all the patients listed above although its magnitude varies. Patient JH, for example, with a particularly mild impairment, shows a reduction in performance from 90% of three-letter words correctly spelled to 70% of seven-letter words correct, whereas patient AS shows a performance reduction from 96 to 44% over the same range.

2.2. Error types

The majority of the errors of GBD patients can be explained in terms of the substitution, deletion or insertion of a single letter or the transposition of a pair of letters, although more complex errors also occur. Patients vary in the relative proportions of these different error types however.

For some patients letter deletion errors predominate (ML, DH, and SE), while some show a predominance of substitutions (LB, FV, CW, and JH). The remainder of the patients mentioned above produce similar numbers of substitutions and deletions. For most patients insertion and transposition errors are less frequent than substitutions or deletions although a fair number of both occur (e.g., LB, 6% insertions and 17% transpositions. AS, 22 and 14%). It is notable that when the distinction has been made (for patients LB, JH, and AS), almost all transposition errors involve the exchange of two letters rather than the simple shift in position of a single letter.

A further detail, the effect of word length on the relative proportions of different error types, is reported for patients AS, LB, JH, DH, and ML. A pattern is apparent for AS, LB, JH, and DH who all show an increase in the relative proportion of deletion errors and a decrease...
in the proportion of substitutions with increasing word length. ML however does not appear to show any trend in these error types, and the patients are variable with respect to the effect of word length on other error types.

2.3. Double letters

An interesting range of errors occurs on double (or geminate) letters—the property of gemination (i.e., doubling of a letter) appears to separate from the identity of the letter being doubled. This has been noted with patients LB, AS, SFI, and HE, and is apparent in several types of error. For example, errors are found where the doubling occurs in the wrong position (e.g., arresi → aressi), the doubling does not occur (attesa → atesa), the doubling occurs in the correct position but with an incorrect letter doubled (troppo → trocco), or where an extra doubling occurs (abisso → abbisso) (examples from the Italian patient LB). The introduction of a doubling into a word that does not already contain one is rare. The Italian patient SFI shows a particularly striking deficit on geminates, with a large number of deletions on doubled letters and relatively few on single letters. SFI’s deficit is limited to spelling, his aural perception and oral production of geminates (which are phonologically marked in Italian) being unaffected. This supports the idea of a geminate representation specific to spelling (Miceli et al., 1995).

2.4. Serial position effects

With only one exception errors for these patients are more common in medial letter positions than at the start or end of a word. Within this overall pattern some patients (e.g., LB and ML) show a peak in errors nearer the start of words whereas others (e.g., JES, AM, AS, and DH) show a peak towards the end. The other patients listed above show more symmetrical serial error curves. The exception to the general rule is FV, who shows no apparent effect of serial position.

2.5. Effect of lexicality

It is part of the definition of GBD that errors on words and non-words should be qualitatively similar, and this is the case for all patients who have been tested in sufficient detail (LB, FV, AS, JH, and SE). However, only SE shows quantitatively similar performance irrespective of lexical status. The other patients show a lower level of performance on non-words compared with words.

2.6. Effect of consonant/vowel status

In those patients where the matter has been reported (LB, AS, JH, HE, FV, and SE) there is a strong tendency for substitution and transposition errors to preserve the consonant or vowel (CV) status of letters. The effect is not absolute in that most patients show less than 100% preservation of CV status; for example, 82% of AS’s substitutions and 62% of his transposition errors preserved CV status.

More recently, a further group of patients have been reported with a deficit which is similar in many ways to that outlined above (Cipolotti, Bird, Glasspool, & Shallice, 2004). These patients, typified by HR (Katz, 1991), BA (Ward & Romani, 1998), and TH and PB (Schiller, Greenhall, Shelton, & Caramazza, 2001), differ from the GBD pattern described above in several ways, however. Most cogently they produce serial error curves with a different shape—the probability of an error increases monotonically from start to end of a word—and most of their errors are deletions, including a large number of a new type of error not seen in “classical” GBD, the fragment (Ward & Romani, 1998)—responses two or more letters shorter than the stimulus. Their spelling is also affected by semantic variables such as concreteness, and semantic errors occur. In the present paper, we will only be concerned with the more ‘classical’ form of GBD of the first group of patients as detailed above. The second form can also be treated within the same general approach, but this is beyond the scope of the present paper, as discussed below.

In the next section, we outline a general approach to serial order in behaviour, before returning to the issue of how to provide a theoretical model for the deficit of GBD patients.

3. A framework for modelling serial behaviour

A central aim of the current work is to relate the problem of serial order in spelling to the more general problem of serial order in behaviour (Lashley, 1951). The benefit of studying spelling in the context of a general theory of serial behaviour is clear: it is important not to have to postulate the existence of highly idiosyncratic mechanisms for such a culturally restricted skill. Conversely, and equally importantly, data from spelling, if they are revealing with respect to general mechanisms, gain an importance they would otherwise lack. To motivate our choice of theoretical framework we begin by briefly reviewing a number of phenomena found across behavioural domains. We then outline the basic features of a theory of serial order (which we will refer to as “Competitive Queuing”) which has previously found productive application in number of these domains. In studies of language and motor skills it is striking that a number of characteristics are common to different types of serial behaviour (Glasspool, 1998). For example.

1. Longer sequences are more error prone, for example in spelling (Wing & Baddeley, 1980) and in recall from verbal short-term memory (Baddeley, Thomson, & Buchanan, 1975).
2. Most errors in serial behaviour involve the production of the correct responses in the wrong order, rather than the production of responses which do not occur in the target (e.g., in speech, Shattuck-Hufnagel, 1979; recall from short-term memory, Aaronson, 1968; and spelling, Wing & Baddeley, 1980). Erroneous items in an utterance may be displaced forwards or backwards over several intervening items, indicating that at some level in the sequence production process an extended series of responses are concurrently present (Lashley, 1951).

3. Most errors occur towards the middle of the sequence. Primacy and recency effects are found in studies of spelling (Caramazza et al., 1987; Wing & Baddeley, 1980), in recall from verbal, spatial and motoric short-term memory (STM) (e.g., Burwitz, 1974; Healy, 1975; Murdock, 1962), and in the “tip-of-the-tongue” state (Brown, 1991).

4. Repetition of particular items or similar segments facilitate errors in speech (Dell, 1984), in verbal short-term memory (the “Ranschburg” effect, Henson, 1998b; Jahnke, 1969) and in spelling (Hotopf, 1980). (Henson, 1998b; notes that this effect is reversed in some situations, notably in the case of immediate repeats or doublings.)

5. Errors tend to preserve important structural constraints within a given domain. In sentence production, misplaced words generally preserve the grammatical status of the target word (Shattuck-Hufnagel, 1979). In speech, slips of the tongue generally result in combinations of sounds which conform to the rules of the speaker’s language (Fromkin, 1971). In recall from verbal STM, order errors often occur between phonemically similar words (Conrad, 1964) and intrusion errors from previous lists respect within-list positions more often than chance (Henson, 1999).

These shared characteristics suggest that similar mechanisms may underlie sequence production in various domains. We now describe one approach which has been widely used in modelling such phenomena.

3.1. Competitive queuing

We will use the term Competitive Queuing (CQ) to refer to a class of models of serial behaviour which has found application in a number of psychological domains (references are given below). Although there are important differences between implemented CQ models, the following three features are typically present.

1. A set of refractory response representations: These constitute a pool of distinct responses or actions from which individual sequences are generated. The nature of the response set depends on the particular problem being modelled. The responses are refractory in that when an item is produced as part of a sequence, it becomes temporarily unavailable for further use.

2. Parallel response activation and activation gradient: Responses in a target sequence are activated in parallel at the beginning of recall, but with a gradient of activation over them such that the sooner a response is to be produced the more active it is. The set of active responses forms the “competitive queue,” as the responses compete for output on the basis of their activation level. The relative activation levels may remain static throughout production of a sequence or they may change over time.

3. A competitive output process: This process has to resolve the response competition in the queue by selecting out the currently most active (dominant) response. As responses are refractory this process also leads to the subsequent inhibition of the chosen response.

Conceptually such models can be viewed as comprising two components: an output mechanism (consisting of the response representations and an implementation of the competitive output process), and an activating mechanism, which is responsible for establishing an appropriate gradient of activation over the output representations. In many implemented CQ models the latter role is played by a set of connectionist weights. It is an abstraction over a potentially complex set of cognitive processes upstream of the output mechanism which may affect activation levels among the output representations.

Models of this form can learn sequences using simple associative learning rules (Houghton, 1990). However, they stand out from the associative tradition in sequence learning in not depending in any way on inter-item chaining, whereby current (or previous) responses cue later ones. Serial order emerges instead from the response activation gradient and competition for output.

The question of whether sequential behaviour is generated by chains of associations linking each response to the next has been vigorously debated for many years. Chaining of associations is a very natural way to imagine serial behaviour originating, but cogent arguments have been made for example by Lashley (1951), Young (1961, 1962, 1968), and Slamecka (1964), that serial verbal learning does not involve any form of inter-item association but instead involves associations between each item and some representation of its ordinal sense.

---

1 The term “Competitive Queuing” was introduced in a specific model of speech production (Houghton, 1990). Although this was not the first model to use the approach (see, e.g., Grossberg, 1978; Milner, 1961; Rumelhart & Norman, 1982) the label is useful for the broader class of models which generate sequential behaviour using the same basic dynamic process. Here, we use the term in this more general sense.
position in the sequence. Similar arguments have been made that other forms of linguistic output, including spelling, are free from associative chaining (see Glasspool, 1998; Houghton & Hartley, 1996). For example, “exchange” errors are common in slips of the tongue, slips of the pen, GBD spelling, and typing, as well as verbal STM. A common type of error has the form ABCDE → ADCBE, where B and D exchange places. Straightforward chaining accounts predict that when the erroneous D is produced in the second position, the next response to be activated would be E, via the D to E association. (Assuming that C is in fact produced in its correct serial position chaining accounts do not then straightforwardly predict why B rather than E should be generated in the fourth position, whereas the “ordinal” approach predicts a “gap” in the sequence at this point which B, only two steps from its natural position, can easily fill.) More generally, the fact that errors in GBD spelling often involve the correct letters in the incorrect order suggests that sequencing of letters in spelling is not a simple case of learning an association between each letter and its predecessor.

The CQ approach naturally lends itself to a representation of sequences in which each item is associated with a particular serial position rather than with the identity of any other item, and this has been seen as an attractive feature in the development of CQ models in a number of psychological domains, including:

- Typing (Rumelhart & Norman, 1982);
- Speech production (Dell, 1986, 1988; Hartley & Houghton, 1996; Houghton, 1990; Vousden, 1996);
- Spelling (Glasspool, Houghton, & Shallice, 1995; Houghton, Glasspool, & Shallice, 1994; Shallice, Glasspool, & Houghton, 1995);

The most common errors occur in CQ models when an active response wins the output competition at the wrong time. In the basic form of the model, this will generally be a response that should have occurred close to the target response, as probability of output depends only on activation level and the strongest competitors to any response are those that should be produced near to it. However, serial order errors in many domains, including spelling as discussed above, indicate that the main competitors to a given target response are not necessarily those that should immediately follow it, but activated responses of the same class as the target. How can such error patterns be understood from a CQ perspective?

### 3.2. Categorical constraints on serial order

When we look closely at specific domains of serial behaviour we often find that there appear to be generalised constraints operating over all instances in the domain. For example, in speech production, the order of phonemes in syllables is highly constrained, both within and across languages, and speech errors have been found to preserve these constraints (Dell, 1986; Fromkin, 1971). The most natural way to express these constraints is typically in terms of a more abstract “schema for order” (Lashley, 1951), in which the category of response which can be produced at any point is restricted to some subset of the responses comprising the behavioural domain. When errors occur in a sequence, the categorical constraints still apply, so that for instance if two items are transposed they will be of the same category. In CQ models, selection of an action for production can only occur when the action wins the activation competition. Any constraint on the set of possible actions at each serial position must therefore be integral to this selection process. Hence, the obvious way in which categorical constraints can be imposed in such a model is by biasing the activation levels of whole classes of response.

The biasing of sets of response representations is most likely to originate within the activating mechanism rather than the output mechanism of a CQ model. Such an effect may arise in two main ways which we have characterised as external and internal (Glasspool & Houghton, 1997). In the external case, the bias comes from an explicit representation of the stereotyped “template” to which a target sequence must conform. Activation of the template is serially ordered, and it sequentially activates or primes whole classes of response. Many activation-based model of speech and language production have this form, e.g., Dell (1986), Dell, Burger, and Svec (1997), Hartley and Houghton (1996), Mackay (1987), Schade and Eikmeyer (1998). In the internal case the bias comes from shared features in the internal representations of items, which lead to interference between similar items (see Glasspool & Houghton, 1997, for further discussion). In the model described in this paper, we present a CQ model of spelling incorporating external serial constraints. The serial template of such a model may be proposed as a theoretical entity in its own right, or may be used as a device to abstract away from the details of any complex regularities within the upstream activating mechanism that are held to systematically affect the excitation of certain classes of response. In the model presented here, we are agnostic about the origin of the proposed template, our interest being initially in the effect rather than the source of response biasing.
Constraints emerging from a biased competitive queue may be either “hard” (that is, inviolable) or “soft” (violable). For example, phonotactic constraints on slips of the tongue appear to be effectively hard constraints, while the CV structure constraints seen in graphemic buffer disorder are of the soft type. A hard constraint on sequence structure imposes a form of serial grammar, allowing symbolic linguistic categories to be represented while maintaining the same simple underlying model of sequence generation. An attractive feature of the activation-based competition used in CQ is that hard-constraints are not necessarily different in kind from other response biases, but simply greater in magnitude. A single mechanism, the biasing of activations in a competitive queue, can therefore in principle account for a wide range of different serial constraints resulting from biases in processes prior to sequential output.

4. Modelling graphemic buffer disorder

The errors of GBD patients are suggestive of the typical pattern of breakdown for CQ systems discussed above. We take this to suggest that GBD originates in a system responsible for the serial ordering of letters in spelling, which operates according to the general principles outlined above. In the current paper, we model this output stage of the spelling system using a CQ approach. We will neither be concerned here with modelling processes prior to the graphemic buffer (semantic and phonological spelling routes, see Glasspool et al., 1995 for discussion) nor with processes assumed to lie subsequent to this stage (such as allographic conversion and motor output).

Modelling work in the CQ framework has typically focussed on the effect of damage to, or disruption of, the sequence generation system itself. An interesting question is what the consequences would be of damage to “upstream” systems, resulting, for example, in an intact GOB operating on degraded input (i.e., sub-optimal activation within the “activating mechanism”). In more recent work, we have begun to investigate this and found an error pattern which is similar to the “variant” form of GBD discussed above—a large proportion of deletion and “fragment” errors, and a serial error curve which increases monotonically rather than being bowed (Glasspool, Shallice, & Cipolotti, submitted). Modelling of these variant patients is beyond the scope of the current paper, however, and we simply note that the general approach used here to model “classical” GBD is applicable, under different assumptions, to the variant form (see, Glasspool et al., submitted, for further details).

The only previous attempt to simulate GBD data is that of Houghton et al. (1994) and Shallice et al. (1995), who adapted the CQ speech production model of Houghton (1990) for the encoding and retrieval of the serial order of letter identities. Damage to the “graphemic buffer” was effected by the addition of random noise to letter activations during recall. The basic model had been developed independently of GBD data, however Houghton et al. were able to model some aspects of the GBD patient data at a gross level. In particular, the model produced qualitatively correct effects of word length and serial position on errors, and the different error types produced showed qualitative similarities to the subject data. While encouraging, the model had a number of shortcomings. In general its performance was considerably poorer than that of GBD subjects, errors increasing very rapidly with word length even for fairly small amounts of noise. Glasspool (1998) discusses other problems with the model, all of which are related to an overly fragile performance in normal recall. In the present work, we therefore start with a more robust model of normal recall while retaining the dynamics of parallel response competition. We address this by improving the positional discrimination of the model, that is, adjacent serial positions within a letter sequence are made less confusable. In addition to the changes required to effect this, the main differences from our previous model are a reduced number of free parameters (which makes it possible to characterise the range of behaviour which the model can produce in a far more systematic way) and the addition of CV information.

Our aims are twofold: First, to develop a model of basic serial output processes in spelling which will provide an explanation for the major features of GBD; and second, to allow for stepwise refinement to accommodate future elaboration of the linguistic processes underlying spelling, so that the basic features of the model do not have to be abandoned in future work in order to account for increasing levels of detail. If our basic proposal is sound—that the gross features of GBD are explicable in terms of a disrupted competitive queue—then we believe that future elaboration will take place mostly in the mechanisms responsible for activating letter representations, rather than in the competitive output mechanism. Such changes should essentially have their effect on the final output through activation biases in the queue, as discussed in the previous section.

The effect of CV status on GBD spelling is a good example: clearly the preservation of CV status in spelling errors implies that CV information is available, but there are a number of possible sources. CV status might be represented separately from letter identity, in an abstract “CV template” for each word (see Caramazza & Miceli, 1990; Dell, 1986; Tainturier & Caramazza, 1996). Another possibility is that letters have a distributed internal representation which includes a CV dimension (see Glasspool, 1998; Glasspool, Shallice, & Cipolotti, 1999). In either case CV information will make itself felt through biasing the competitive queue—in the former
case through the global biasing of all C or V responses by a template (an external constraint), and in the latter through partial activation of items sharing the same CV status as the target due to their similar internal representations (an internal constraint).

Of course, spelling is no doubt influenced (subtly and not so subtly) by all manner of other linguistic regularities besides CV status (as well as by other factors such as deliberate and idiosyncratic spelling strategies—see Section 6). At present, however, it is unrealistic to contemplate addressing many such effects in a simplified computational model. In the current work, we wish to focus on those effects which we believe can be explained directly in terms of a disrupted competitive output selection mechanism. In this respect the separation of activating processes from selection mechanism in the CQ approach is a positive advantage. It seems reasonable to assume that regularities arising in the lexical and phonemic spelling routes prior to the graphemic buffer will have their effect on spelling through the biasing of letter activation levels rather than by altering the fundamental mode of operation of the serial output mechanism. We can therefore have some confidence that the basic findings from our simplified model of queue disruption will generalise to more complex models which take a more detailed view of the factors affecting letter activation.

This confidence is based on the assumption that biasing the competitive process in a CQ model will impose categorical serial constraints without either impairing normal performance or leading to new patterns of errors which are not attested to in the data. To test this assumption, and to address the major linguistic regularity shown in GBD spelling, we include CV information in the model developed below. So as to be clear about what aspects of the model relate to which effects (and in particular which are due to the basic sequencing mechanism) we will do this using an external CV template. However, this is intended to be representative of the effect of CV information (and, by extension, other types of linguistic information) on the CQ model, from whatever source it may come, providing only that any such information systematically affects the activation of certain classes of letter representations at the output stage of the model. We will be concerned with the process of generating a spelling for a known word from memory, and aim to account for the following features of GBD spelling:

1. Word length effects.
2. Serial position effects.
3. The occurrence of insertion, deletion, shift, exchange and substitution errors.
4. The types of error made by GBD patients on double (geminate) letters.
5. The selective preservation of CV status in errors.
6. Qualitatively similar behaviour on word and non-word material.

4.1. Architecture and operation

This section gives an overview of the structure and operation of the model. Full implementational details are given in Appendix A. The CQ approach does not in itself imply any particular type of implementation. However, since it centrally involves associations between items with variable activations a connectionist formalism is convenient (most implemented CQ models are connectionist in nature). Fig. 1 shows the architecture of the model, which comprises four main layers of connectionist nodes: the Sequence layer, the Item layer, the Letter layer, and the Filter layer.

Glasspool (1998) discusses a number of shortcomings of the CQ spelling model of Houghton et al. (1994) and Shallice et al. (1995), and relates these to poor discrimination between successive sequence positions in the system responsible for activating letter nodes. The most significant change we wish to make with respect to that model is thus to increase the positional resolution of the sequence generation system.

Improving positional resolution in CQ models has been approached in two ways (Glasspool, 1998). CQ models often employ some form of time-varying input signal from which an indication of the current sequential position is derived during sequence generation. The first approach to improving positional resolution has been to make successive states of this time-varying signal more distinctive, by making the signal itself more complex. Thus, rather than comprising, for example, a single activation value which varies smoothly over time (e.g., in Page & Norris, 1998), additional activation values with different time-varying profiles may be added (e.g., in Burgess & Hitch, 1992; Glasspool, 1995; Brown et al., 2000) to produce a more complex multi-element signal with more distinctive successive states.
The alternative approach is to retain a very simple time-varying signal but to use a more powerful mathematical function to distinguish its successive states. The only fully implemented model to date that takes this approach is Henson’s (1998a) SEM model, which does not use a connectionist implementation. However, Houghton (1994a, 1994b) suggests improving the positional discrimination of a connectionist CQ model using the second approach by combining a simple activating signal with a powerful “activating function” for the connectionist nodes representing individual items in a sequence.

Each of these approaches leads to an increase in the complexity of the activating mechanism. The former approach requires a more complex time-varying representation of sequence position. The latter approach has the problem that, since the improved discrimination is being applied to a very simple representation of sequence position, repeated items can become difficult to represent in a simple connectionist implementation (a single item would require more than one representation of its serial position to be stored in the same small set of connections to a simple activating signal, whereas in the former approach different subsets of the larger number of connections to a more complex activating signal can identify separate occurrences. See Glasspool, 1998). A solution is to make a separation between the occurrence of an item and its identity, such that two different tokens representing two separate occurrences may be bound to the same letter. Related models have accepted the costs associated with a “type-token separation” approach, notably those of Page and Norris (1998), and Dell (1986, 1988). Additionally, recent evidence from the field of verbal short-term memory suggests that a type-token distinction exists in the sequence generation processes underlying tasks in that domain (Henson, 1999). With this in mind, and given the desirability of testing the second approach to improving positional discrimination which has yet to be tried in an implemented connectionist model, we adopt the second approach in combination with a type-token distinction in the current model.

The first layer of nodes in the model, the sequence or control level, implements the time-varying representation of sequence position and contains units that stand for whole words (or possibly, in the case of longer words, subword chunks). Each word is associated with an Initiate–End node pair whose activation changes during learning and recall. The Initiate node begins with high activation at the start of the word which decreases as spelling progresses, while the End node activation starts low and increases. Together the activation of the two nodes forms a two-dimensional vector which rotates (roughly) through 90° as recall progresses. The position of this vector gives an indication of how far recall has progressed. Note that the signal is more similar to itself at nearby points in time. This form of coding of relative serial position was first used by Houghton, 1990; in a model of speech production, and without knowledge of GBD data, and was used again in the model of Houghton et al. (1994). We continue to use the same form of positional representation in the present model, although other types of representation may provide essentially the same positional information.

The second layer of nodes, the item layer, implements the “type-token” distinction referred to above. Each item node acts as a place-holder for a different response. During recall, an item node achieves its maximum activation when the Initiate and End node activations are in the state they were in at the corresponding sequential position during learning. In the model only a single Initiate/End pair and a single set of item nodes is included. In practice an Initiate/End pair would be required for every sequence (word) to be stored, and in the simplest interpretation of the model, a separate set of item nodes would also be required for each word. (This therefore constitutes a localist representation of word spellings which might be criticized on grounds of the neurological plausibility of the large number of individual representations required. Page, 1997, discusses some implications of localist representations, including their neurological plausibility. One way in which the requirement for separate I/E and item nodes for each word can be relaxed is to allow distributed representations at this level of the model. This is discussed by Glasspool, 1998 and Glasspool et al., 1999, and is beyond the scope of the present work.)

The next layer contains letter nodes, each representing a single letter. These are activated by the item nodes via excitatory connections with fixed weights, and it is the arrangement of these connections which defines which sequence of letters will be produced by the model. Letters may be repeated within a word by connecting two or more item nodes to the same letter node.2 However, letter nodes are refractory—they are inhibited after the corresponding letter has been produced by the model, and recover slowly from their inhibited state. Inhibited letter nodes are more difficult to re-activate. (The type-token distinction adopted in the present model does not, therefore, allow it to avoid the usual limitations on repeated letters imposed by the CQ approach—discussed further below—as it operates above the level of the refractory letter nodes and the competitive output system.)

Response competition takes place in a dedicated sub-system, the competitive filter. This comprises a field of nodes with strong mutually inhibitory and self-excitatory connections such that they form a “winner-take-all” competitive system, which reinforces the node which

---

2 This is similar to an arrangement suggested by Milner (1961) in a model of short-term memory.
starts with the highest activation and extinguishes activation in all others (see Houghton, 1994a, 1994b; Houghton & Tipper, 1996, for further discussion of this selection mechanism). These nodes are connected one-to-one to the letter nodes and identify the most active letter at each time-step. The winning letter is selected for output, and the corresponding letter node is inhibited by setting its activation to a negative value from which it slowly recovers. To simplify the model, the competitive filter is simulated in the current implementation by a peak-picking algorithm.

The refractory behaviour of nodes representing sequenced items is central to the CQ account of serial behaviour. We see this refractoriness as directly tied to the competitive output selection process in that it is the winner of the output competition which is subsequently inhibited. In the current model, we separate item nodes, representing sequence positions in the abstract, from letter identity nodes, and the question thus arises of which set of nodes should be subject to competition and inhibition. We assume here that the item nodes are conceptually part of the activating mechanism of the CQ model rather than the output mechanism, and this implies that refractory inhibition should apply to the letter nodes. This accords with the observation that although in many forms of serial behaviour, spelling included, the majority of errors involve items present within the target sequence, nonetheless the remaining errors—a sizeable proportion in many cases—involves items from outside the sequence ("item" rather than "order" errors). This is most straightforwardly explained by locating the competitive process at the level of item identities (letter nodes) rather than sequence positions, allowing letters from outside the target word to participate in the noisy competition for output.

Refractory competition among letters means that it is not possible to produce a letter twice in a row. This is in line with most CQ models which require an additional mechanism for the generation of immediate repeats. Indeed, a general prediction of such models is that repetitive behaviour must represent a distinct behavioural mode. Interestingly, the types of error commonly made on double responses in tasks such as typing and writing have led theorists to propose on empirical grounds that close repeats involve a specific mechanism or schema, which is subject to errors in its positioning (see for example Rumelhart & Norman, 1982). Why immediate repetitions should require special handling has generally remained an open question. Paradoxically, therefore, rather than being a disadvantage, the need to invoke such additional mechanisms allows a principled account to be given for the distinctive behaviour of double letters (Glasspool et al., 1995; Houghton et al., 1994). In the current model double letters are dealt with by a geminate mechanism, implemented as a geminate node which is driven by the same control signal as the letter nodes and must pass an activation threshold to be triggered. Triggering causes the letter currently being produced to be doubled. Like letter nodes the geminate node is inhibited following output.

While some form of doubling schema is a clear prediction of the CQ approach the currently implemented mechanism is no doubt simplistic. Multiple geminates in words such as bookseller are possible, but only with sensitive setting of parameters. The simplified mechanism is incapable of producing double geminates, e.g., in balloon. To avoid biasing the results due to these limitations, words containing more than one geminate feature were excluded from the test corpus for the simulations reported here.

During recall a "CV template" biases the activations in the competitive queue so as to favour consonants or vowels at different points in the recall process. A constant amount of activation is added to all vowel letter nodes if the CV template indicates that a vowel should be produced, or to all consonant nodes if a consonant should be produced. The CV status of each letter in a word is encoded by the model during learning. Whatever its source, the assumption that serial constraints in a CQ system amount to biasing the output competition implies that an abstract CV template aligned with the target word will provide a first-order approximation to the effect of CV information.

4.2. Overview of operation

The operation of the model can be divided into learning and recall phases (see Appendix A for full details). During learning the letters of the target word are presented one by one in the correct sequence. As each is presented a new item node is activated along with the appropriate letter node. During presentation the Initiate and End nodes change their activation state as described above.

Three sets of connections may be altered during learning.

1. The connections between the Initiate and End nodes and the item nodes.
2. The connections between the activated item node and the letter node representing the presented letter. Hebbian learning on these connections associates a letter with a particular sequence position.
3. If a letter is doubled, Hebbian learning on the connection between the active item node and the geminate node associates the geminate schema with this position.

During recall, the Initiate and End nodes repeat their, respectively, falling and rising activation patterns. This produces parallel activation of item nodes, which in turn generates a pattern of activation over the associated
letter-type nodes. The competition amongst response types is resolved by the competitive filter, subject to the additional influence of the CV template. Once a winning letter is selected its representation at the letter node level is inhibited and thereafter recovers slowly. Spelling stops when no letter node has an activation level exceeding a pre-set threshold.

In modelling damage to the graphemic buffer we add a degree of random noise to the output competition. We would argue that this is the least theoretically specific manipulation which could be made to this model to disrupt its behaviour. That is, disruption of such elements as the Initiate–End signal could be criticised on the grounds that an entirely hypothetical construct is being manipulated. By contrast, no one is likely to deny that the spelling of a word must involve the activation of the letter identities of successive responses. The addition of noise simply makes this activation process, however it is achieved, less reliable than normal. This is the only manipulation made in attempting to model GBD.

4.3. Relation to the overall spelling framework

How would the current model fit into the overall structural model of the spelling system discussed above? Letter sequences are well learned and presumed to be permanently available. The model outlined here can thus be seen as an implementation of the lexical spelling route. The model includes a complex of nodes—the Initiate/End pair and the item layer nodes—which must be separately instantiated for each known word. This implies a non-semantic lexicon which would correspond to the graphemic output lexicon on the overall spelling framework. The letter nodes are shared by all words and may thus be considered part of the graphemic output buffer. In fact on the present model the output buffer comprises only the letter nodes and the competitive filter, and should thus properly be considered a sequence generation mechanism rather than a buffer in the usual sense. This is considered further in Section 6.

The problem remains of how the output of the assembled spelling route is to be integrated into the final output of the system. One solution is to assume that the current model, as well as having the ability to form long-term representations for familiar words, can also rapidly learn temporary representations for novel words. The process of spelling a non-word would then involve the generation of a spelling by a sound-to-spelling system, the rapid generation of a temporary representation for that spelling by the CQ system, followed by the output of that spelling in the same manner as for a known word (this approach is taken by Glasspool et al., 1995). This putative mechanism is somewhat unwieldy, although it does allow a candidate explanation for the difference in performance, but not qualitative pattern, of GBD patients on words and non-words: words may acquire a more robust representation than non-words can achieve in the face of a similar level of disruption. We return to the issue of integration between the routes and non-word representation in Section 6.

4.4. Fitting the model to patient performance

The model contains eight free parameters plus the noise level used to simulate damage. This is a low number compared with Houghton et al. (1994). Our approach is therefore to initially set the parameters by hand to approximate the performance of a specific patient, and to freeze these parameter settings across all of the main simulations. We then separately address the important issue of the parameter-dependence of the model, in other words the range of parameter values over which the model can explain the qualitative features of the data. This is done through an extensive parametric test reported in study 6 of the next section.

The aim for this model is not to perfectly match the performance of a particular GBD patient—indeed, it would be surprising if a model of the serial output process, disrupted only by the addition of unstructured noise, were able to closely match performance in an area such as spelling, which is surely influenced by a variety of idiosyncratic and strategic factors over and above basic sequential mechanisms (Shallice et al., 1995). The aim in these simulations is to produce a “generic GBD” performance. Since English words are used in the test corpus (as detailed below) we aim for a closer fit to the English patient AS.

5. Simulations

We aim in this section to test the model comprehensively in order to find its limits as a basic framework for serial processes in spelling. The simulations are carried out on a corpus of English words taken from the Oxford Psycholinguistic Database (Quinlan, 1993). It is important to start by assessing the ability of the intact model to account for normal spelling. The model was therefore initially tested on all 33,259 words in the database. The database contains a number of long and infrequent words and the model was not expected to be able to spell every one perfectly—longer sequences, especially those with repeated items, are more difficult for a CQ system to produce. However, only 906 words (2.7%) could not be reproduced in the absence of noise, and as expected these were all long words: 3 eight-letter words (0.06%), 26 nine-letter words (0.6%), and 877 of length 10 or more letters (12%). We return to the issue of long words in Section 6, but we take this test to estab-
lish that the model provides a reasonable basis for normal spelling.

The remainder of the simulations consider the performance of the damaged graphemic output buffer. For these simulations a test corpus was compiled excluding the minority of words which could not be spelled by the intact model. Words with more than one double letter were also excluded. Four thousand four hundred and thirty-one words of six letters formed the core of the corpus, as much of the detailed error analysis is carried out on six-letter words for comparison with experimental data. To these were added a randomly chosen subset of words of different lengths: 500 words of each length from 3 to 5 letters and from 7 to 12 letters, 69 2-letter words and 3 of one letter. Data in studies one to five were collected over 20 passes through the full test corpus of 9003 words.

5.1. Study 1—Basic performance

The most basic aspect of the model’s performance is the probability of correctly spelling a word of a particular length in the presence of noise. This study characterises this basic level of performance in the model and compares it with the spelling performance of GBD patients. Fig. 2 shows the overall percentage of correct spellings produced by the model for each word length in the test corpus at each of three values for the noise magnitude. Performance is compared with that of GBD patients AS (Jonsdottir et al., 1996) and LB (Caramazza et al., 1987), whose deficits are of typical severity, and JH (Kay & Hanley, 1994), who shows a relatively mild deficit. A noise level of ±0.422 provides a close fit to AS’s performance on 4- to 7-letter words. A reasonable fit can be obtained to patient JH with a lower value of ±0.32. Both AS and LB appear to show a steeper decline in performance at longer word lengths (especially on 8-letter words) than predicted by the model. It is however, possible that this may reflect a need for qualitatively different processing strategies for long words (e.g., the need to “chunk” longer letter sequences). This would be consistent with the intact model’s relative difficulty with spelling long words. For the remainder of this section the noise level used in matching patient AS is retained as a default value.

Longer words are more error prone. Two factors contribute to this effect: First, a larger number of letters provide more opportunities for error. The second factor is more interesting and more particular to this model. In the model, the more letters there are in a word the more separate relative positions have to be distinguished in the weights linking the Initiate–End nodes to the item nodes. This weight space is fixed, and hence the more items there are in the word the more crowded the space becomes, and nearby positions in the sequence are represented by closer points in weight space. During recall this leads to the gap in activations of successive item nodes becoming smaller, and the target letters are consequently less reliably distinguishable in the face of noise.

5.2. Study 2: Error incidence

Turning now to simulation of the GBD error data, we first look at the kinds of error made by the model under the influence of noise. The errors made by GBD patients AS (Jonsdottir et al., 1996) and LB (Caramazza & Miceli, 1990) have been analysed in some detail. Most of this analysis has taken place on words of six letters, and we have made a similar analysis of the errors made by the model on six-letter words.

Following the experimental studies we analyse the errors made by the model into five categories: insertions (e.g., ABCD → ABXCD), deletions (e.g., ABCD →
ACD), exchanges (e.g., ABCD → ADCB), shifts (e.g., ABCD → ACDB), and substitutions (e.g., ABCD → ABXD).\footnote{One slight difference between the analyses of the patient data and the model’s output is due to the very large number of errors produced over the model’s large corpus, which makes manual analysis of errors impractical. We have thus developed software tools which automatically classify errors. However, it is difficult to consistently analyse responses which contain more than one error using automatic algorithms, so we limit our analysis to those responses which contain only a single apparent error. Some of the responses classified in the GBD studies contained more than one individual error but the majority did not, and we do not therefore believe that this will lead to a major discrepancy between the analyses of the experimental and modelled results.} Insertions and substitutions may involve either new letters not present in the target word or the duplication of letters already present. Table 1 shows some examples of errors produced by the model.

Errors occur in a CQ sequence generation mechanism when, at a particular point in sequencing, the “target” sequence element (letter, in this case) for that position is not the most active element. This occurs in the present model because of the addition of random noise, so the probability distribution determining which particular incorrect letter is produced will depend on the gradient of activations which holds over the letter nodes at that point—the more active a competitor letter, the more likely it is to be produced instead of the target letter. Because noise also affects letters not present in the target word, erroneous letters may come from within or without the word (although letters within the word will be more active and thus more likely). An insertion error occurs when, following the erroneous letter, sequencing continues with the target letter that should have been produced in the error position (each subsequent letter is then produced one position too late). A substitution results when sequencing continues with each subsequent letter produced in its correct position. A deletion may occur when the erroneous letter is the letter following the target letter, and sequencing continues correctly from that point onwards (each subsequent letter appearing one position early). An exchange error starts when a letter is produced too early, and subsequent letters appear in their target positions. When the position of the anticipated letter is reached it will still be inhibited following its earlier production, and a strong competitor in this position will be the letter erroneously passed over earlier. Which of these possibilities actually occurs in a given error is dependent on a rather complex set of interacting factors, however, which makes formal analysis difficult. Some of these factors are considered in Section 6.

Caramazza and Miceli (1990) introduce a scheme for identifying the number of errors occurring at each serial position within words which we adopt here. Points are allocated to particular serial positions when errors occur. In the case of substitution errors the letter position at which the error occurred receives one point. Deletion errors receive one point in the position from which the deleted letter originated. Insertion errors score half a point each in the letter positions before and after the inserted letter. Exchange errors result in two incorrect letter positions, each of which scores one point. Shift errors are scored as a combined deletion and insertion, thus one position receives one point and two receive half a point each. Using this scheme it is possible to score each serial position for the likelihood of an error occurring. Fig. 3 shows the resulting overall serial position curve for single-error responses on six-letter words.

The model shows a higher incidence of errors in medial positions than at the start or end of words. The reason for this is that the I–E timing signal changes more rapidly near the start and end of the sequence than in medial positions, and thus in the middle of the word, consecutive letter positions are less well discriminated. For comparison, the equivalent curves for GBD patients AS and LB are also shown. Both patients show a clear increase in accuracy towards the start and end of words, although both curves peak more centrally than does that of the model.

Looking in more detail at the nature of the errors, Fig. 4 shows the serial error curves from the model indi-

<table>
<thead>
<tr>
<th>Error type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Insertion</td>
<td>devote → devoxetine</td>
</tr>
<tr>
<td>Deletion</td>
<td>patchy → pathy</td>
</tr>
<tr>
<td>Exchange</td>
<td>heroic → horeic</td>
</tr>
<tr>
<td>Substitution (anticipatory)</td>
<td>canary → carary</td>
</tr>
<tr>
<td>Substitution (perseveratory)</td>
<td>sunday → sundas</td>
</tr>
<tr>
<td>Substitution (of letter from outside word)</td>
<td>campus → campos</td>
</tr>
<tr>
<td>Shift of geminate feature</td>
<td>button → buton</td>
</tr>
<tr>
<td>Substitution of doubled letter</td>
<td>grassy → grammy</td>
</tr>
<tr>
<td>Loss of geminate feature</td>
<td>accent → acent</td>
</tr>
<tr>
<td>Addition of geminate feature</td>
<td>oddity → oodity</td>
</tr>
</tbody>
</table>

Table 1. Example errors produced by the model.

\[\text{Fig. 3. The incidence of single-error responses made by the model at each serial position in six-letter words, given in terms of the error points awarded by the scoring procedure of Caramazza and Miceli. Equivalent curves are shown for patients AS and LB.}\]
vidually plotted for the five major error types. Deletions, substitutions, shifts, and exchanges all peak medially. This is also true, for example, of both AS and LB. Interestingly, the “tail” of high incidence for substitutions towards the end of the word shown in Fig. 4 is also a feature shown by AS (Jonsdottir et al., 1996, Fig. 3). AS shows insertions increasing to a peak in the final position, but with a subsidiary peak in the middle of the word, and the model also shows a raised insertion rate towards the end of the word. However, the low rate of insertions in the model compared with that for the patients is a potential problem for the model. We return to this issue in Section 6.

Fig. 5 compares the overall incidence of the different error types produced by the model with those of GBD patients AS, LB, JH, and HE. The patients themselves are somewhat variable in the pattern of error incidences; matching the pattern of any particular patient accurately was not therefore an aim of the model. However, some regularities are apparent. For these patients the most frequent type of error is substitution. The least frequent type of error for AS, LB, and JH is the shift (the two are not noted separately for HE). For these patients deletions are more frequent than either insertions or transpositions. With the default parameters the model captures this general pattern. As shown later in study 6, this aspect of the model’s performance is affected to some degree by the particular parameter settings used. The relative proportions of error types are also affected by the equations governing the activation of the letter nodes (see Section 6). We therefore, confine ourselves to noting that, with appropriate parameter settings, the model is capable of capturing some general features of the error pattern which are common to a number of GBD patients.

Finally, an apparent similarity across several GBD patients is that the relative proportion of deletion errors increases with increasing word length, while that of substitutions decreases. Table 2 shows the effect of word length on error proportions for the model. The model shows the opposite trend, with deletion errors decreasing and substitution errors increasing as a proportion of all single-error responses with increasing word length. Although, there is some variability among patients, it seems that at this level of detail the error mechanisms in the model do not fit well with the experimental evidence. We return to this question in Section 6, where alternative mechanisms are proposed for the occurrence of some types of error which may allow a better explanation for these trends.

5.3. Study 3: Behaviour of doubled letters

This study compares the model’s performance on words with and without double letters (“geminate” and “non-geminate” words). A geminate word is treated as a word one letter shorter and without the doubling, with separate concurrent representation of the doubling (“geminate feature”) by the triggering of the geminate node at the appropriate point. For the letter sequence itself the error rate will thus be less than would be expected for a non-geminate word of the same length. However, the geminate node is itself subject to noise and does not always trigger correctly. The additional error rate due to noise on the geminate node and the lower error rate intrinsic to the shorter letter sequence tend to counteract each other, the overall error rate depending on the relative strengths of the two. In all other simulations the noise applied to the geminate node has the same magnitude as that applied to letter nodes. However, it is interesting to examine the effect of varying the relative noise levels on letter and geminate nodes. Fig. 6 plots the percentage correct geminate words against word length for various values of the parameter “geminate noise factor”, which scales the level of noise in the geminate system.

Fig. 6 shows (broken lines) that with the same magnitude of noise applied to the geminate node and letter
nodes the error rate on geminate words is slightly higher than that for non-geminate words of the same length. GBD patients vary on this comparison. The English patient AS produces approximately the same rate of errors on geminate words as on non-geminate words (Jonsdottrir et al., 1996), while Caramazza and Miceli (1990) found that their Italian patient LB performed considerably better on geminate words than on non-geminate words. Fig. 6 shows (solid lines) that with a value of 0.8 of the standard noise level performance on geminate words closely matches that on non-geminate words, as is the case for AS, while with a lower value of 0.5 performance on geminate words approximately matches that for non-geminate words one letter shorter in length, which is the case with LB on six-letter words (the only length for which there is precise data).

How might this manipulation relate to the spelling system? One straightforward possibility is that this simply reflects patient differences, slight differences in the location of lesions affecting the degree of damage to the geminate system. A more interesting possibility is that it might reflect differences between spelling in English and Italian. Two differences seem suggestive—First, geminate vowels occur in English spelling but are rare in Italian (those which do occur are mostly at morphological boundaries which could provide additional cueing). Taking advantage of this fact would rule out a whole class of errors involving incorrect binding of the geminate feature to consonants, which could reduce the error rate on geminates in Italian. Second, in “standard” Italian doubled consonant letters always correspond to a phonological difference, whereas in English this is not so, e.g., s in *this* vs. *miss*, m in command vs. *demand*; e in scene vs. screen. This potential phonological cueing as to the presence of a doubled letter might be enough to make geminate spelling less error prone in Italian than in English if any residual ability to use phonological information remained. However, these possibilities must be treated with care. There is no evidence that LB is able to use phonological cueing in other aspects of his spelling (Caramazza & Miceli, 1990). Furthermore, the Italian patient SFI of Miceli et al., 1995 appears to show worse spelling on geminate than non-geminate words. More empirical evidence, and a more detailed model of the geminate mechanism, may be required to resolve this issue.

Table 3 summarises the characteristics of GBD errors which appear to result from errors in the production of a geminate feature, and compares the errors made by the model in triggering the geminate mechanism.

A quantitative fit to the data in this area was not an aim of the model. However, some qualitative points emerge. The majority of errors involve the movement or deletion of the geminate feature in the model, which is in agreement with the data (although qualitatively only—the model considerably overestimating the frequency of geminate deletions). The patients make essentially no errors in which a double letter is introduced into a non-geminate word, and the model agrees on this point also. These qualitative effects are straightforward consequences of the geminate mechanism. The inhibition of the geminate node after it has triggered makes it unlikely that it will be triggered more than once in the same word. In non-geminate words the geminate node is completely inactive in the absence of noise, and the presence of noise alone is unlikely to trigger it.

The appropriate performance of the geminate system on these data is encouraging, but clearly a more comprehensive model of the geminate mechanism is required.

<table>
<thead>
<tr>
<th>Word length</th>
<th>Insertions (%)</th>
<th>Deletions (%)</th>
<th>Exchanges (%)</th>
<th>Shifts (%)</th>
<th>Substitutions (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 letters</td>
<td>8.3</td>
<td>55.4</td>
<td>1.4</td>
<td>0</td>
<td>34.9</td>
</tr>
<tr>
<td>6 letters</td>
<td>0.4</td>
<td>27.2</td>
<td>24.6</td>
<td>2.4</td>
<td>45.5</td>
</tr>
<tr>
<td>8 letters</td>
<td>0.3</td>
<td>14</td>
<td>27.8</td>
<td>5.4</td>
<td>52.5</td>
</tr>
</tbody>
</table>

Figures shown are percentages of single-error responses.

Table 2
Effect of word length on error proportions in the standard model

5.4. Study 4—Effect of lexicality

The effect of lexical status is not directly included in the model. GBD patients produce qualitatively similar but usually quantitatively worse performance on non-word stimuli than on words. It is not obvious, however, that manipulations which affect the overall performance of the model will not also disrupt the qualitative error pattern. For example, Glasspool (1998) shows that a straightforward manipulation to our earlier spelling model (Houghton et al., 1994) intended to model the word/non-word distinction (the reduction of supervised practice) significantly changes the pattern of relative proportions of different error types. One way to approach the distinction, as discussed above, is to simply assume that non-word stimuli are less robust in their representation than words. This would correspond on the model to non-words facing an increased level of disruption from noise compared with words. Glasspool (1998) explores a number of manipulations to the basic model and shows that an increase in noise disruption stands out in preserving qualitative features of the error pattern while reducing absolute accuracy.

Fig. 7 shows the overall performance of the model with a slightly higher noise level of ±0.46 compared with the standard level of ±0.422. As expected, performance is uniformly worse for the higher noise level, and is close to that of both patient AS and LB on non-words.

It is hardly surprising that an increase in noise level, corresponding to less robust non-word representation, leads to poorer performance. The important factor is the preservation of the overall qualitative pattern of errors under this manipulation. Fig. 8 and Table 4 compare the relative proportions of the different error classes and the geminate error pattern, respectively, for standard and high noise conditions, and confirm that qualitative behaviour is similar under both normal and high noise conditions.

5.5. Study 5—Effect of CV information

The previous simulations have demonstrated that the model when disrupted displays the basic characteristics of GBD. We now examine the effect of providing CV status information to the spelling process. The errors produced in study 2 were classified according to whether CV status was preserved or not; that is, whether each erroneous letter had the same CV status as the target letter for its position. Fig. 9 compares single-error responses in which CV status was preserved with those which violated CV constraints for the key error types of exchanges and substitutions. As expected the CV template constrains errors, with the majority of errors preserving CV status. However, we had not expected the simple availability of CV information to
produce the observed difference in strength of preservation between exchanges (80.3%) and substitutions (97.2%). The higher rate of CV preservation for substitutions than exchanges is shown by both AS and LB. On the model this is due to the fact that exchanges are considerably more likely between letters which are close together (and thus are close competitors in the competitive queue). The resulting tendency to exchange neighbouring letters of different CV status can sometimes overcome the CV bias.

The strength of the input from the CV template to the letter selection mechanism is a parameter of the model, and varying it results in different levels of CV preservation. A value of 0.15 gives a preservation rate of 62% for exchanges, 93% for substitutions (cf. AS: 62% exchanges, 85% substitutions). A value of 0.25 gives a somewhat higher preservation rate of 90% for exchanges, 98% for substitutions (cf. LB: 91 and 99%, respectively). This parameter is a theoretically neutral way to model any difference in the salience or availability of CV information. This might reflect differences in the degree of damage between patients, or it could correspond to language-specific differences in the salience of the CV distinction or the ease of incorporating residual phonological information in spelling (Jonsdottir et al., 1996). We would reiterate however that we do not aim with the current version of the model to account for the origin of CV biasing (or of any other linguistic effects in spelling). We limit ourselves here to demonstrating that biasing the activation gradient prior to competitive output selection has the expected effect on errors, and observing that the gross features of GBD which we take to result from a disrupted CQ process can thus be studied to a first approximation without accounting in detail for the origin of linguistic serial biases. We need only make the assumption that linguistic information has its effect on spelling primarily by biasing activation in a competitive queue.

The incorporation of CV status information in the model allows the preferential preservation of CV status observed in the errors of GBD patients to be modelled. The incorporation of such information is driven by empirical evidence, however, and the question arises whether the availability of this information to a spelling system has any practical utility—in other words, is spelling performance improved by such information? Fig. 10 shows the effect of the CV bias parameter on the performance of the model. Increasing the level of template influence improves the accuracy of spelling in the face of the same level of noise disruption. Intuitively, the effect of the bias is to weaken the degree of competition from letters of opposite CV status, while maintaining the same level of competition from letters of the same CV status. The overall effect of this depends on the CV structure of individual words, and changes from...

<table>
<thead>
<tr>
<th>Error type</th>
<th>Model</th>
<th>Standard noise level (%)</th>
<th>High noise level (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The geminate feature shifts</td>
<td>23</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td>A doubling occurs in the correct position, but the wrong letter is doubled</td>
<td>12</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>The geminate feature does not occur</td>
<td>63</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>A new geminate feature is introduced into a word which already contains a doubling</td>
<td>2</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>A new geminate feature is introduced into a word with no doubling</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>
letter to letter. Fig. 10 demonstrates that the availability of CV information during spelling production is functional for this model.

5.6. Study 6—Parameter dependence of model behaviour

Formalisation of complex models of psychological processes inevitably introduces free parameters which scale the size of various processes and interactions. The need to fix parameters to produce concrete simulations can however lead to accusations of “curve fitting.” In general, the best strategy is to set parameters to generate a particular level of general performance, and then keep them fixed for all subsequent detailed explorations. This is the strategy pursued in the simulations above. However, in assessing a model it is most important to analyse how sensitive its various empirically desirable features are with respect to parameter variation. If we distinguish between the “robust” and “fine” behaviour of a model, the latter being highly parameter dependent and the former not, it is generally on the basis of the robust behaviour that strong theoretical claims can be made.

The model contains eight free parameters (plus the noise level) which have been set manually to give good spelling performance in the absence of noise and an approximate match to GBD patient AS in the presence of noise. Unless otherwise stated the parameter settings have remained fixed for all studies. Here, we carry out a comprehensive study of a large portion of the model’s parameter space to assess the sensitivity of the model to parameter variation. To make this tractable it is necessary to limit the number of parameters which are varied, and we have chosen for investigation the six parameters which have the most substantial effect on the basic operation of the model. Of these, two affect the inherent accuracy of the positional cueing of letter activation by the Initiate–End context signal (parameters $\delta$ and $c$ in Table 7); another three affect the detailed dynamics of the letter node activations (parameters, $g$, $r$, and $inh$ in Table 7); and the sixth the strength of the CV bias ($B_{CV}$). Each parameter was varied in 5 steps between half and twice its default value. With six parameters this produces $5^6 = 15,625$ parameter sets. The model was tested with each parameter set on two complete passes through the test corpus of 9003 words, a total of over 280 million runs of the model. This large number of runs clearly necessitated that testing and analysis of the models performance was automated.

Parameters $c$, $inh$, and $B_{CV}$ are varied by multiplying their values by 0.5, 0.75, 1.0, 1.5, and 2.0. Parameters $\delta$, $g$, and $r$ may only vary between 0 and 1, and are thus treated by multiplying the difference between the parameter value and 1.0 by the same set of values. Error distributions are best compared when overall performance is as equal as possible, hence for each set of parameter values noise was normalised to produce as near as possible an overall performance of 54% correct on six-letter words, the level achieved with the default parameters. In 20% of cases it proved impossible to achieve this level of performance even without noise, however, this was due to extreme parameter values. Over a narrower range of variance, 0.75–1.5 times the default values, only 4% of cases failed to achieve the baseline performance. Those parameter sets that could not support this level of performance were discarded.

The model’s performance was automatically analysed for the presence or absence of five major features.

1. Word length effects. An effect was taken to be shown where performance declined monotonically for words of 2, 4, 6, 8, 10, and 12 letters.

2. Serial position effects. The effect required was a peak error rate in a serial position other than initial or final positions.

3. Ranking of incidence of error types. While patients vary considerably on this pattern we were interested in the stability of the gross ranking of error proportions seen with the default parameter values (study 2), with substitutions the most frequent errors, exchanges, and deletions intermediate, insertions lower than either and shifts least.

4. Preservation of CV structure in errors. An effect was taken to be shown if the number of errors preserving CV structure was at least 10% greater than those not preserving it.

5. The ranking of geminate error types as compared to GBD patients AS and LB (the only patients for whom this has been studied). The pattern required was that shifts and deletions of the geminate feature should both be more common than the introduction of new geminate features.

Table 5 shows the model’s performance on each of these criteria over the full parametric study. In addition, the results over the smaller parameter space between 0.75 and 1.5 times the default value are listed separately to provide some indication of the effect of extreme parameter values.

As can be seen, properties 1, 2, and 4 of the above list are very robust, all being present together in 94% of cases in the full survey, and 99% over the narrower range of parameter variation. With respect to property 3, ranking of error types, this turns out to be considerably more parameter dependent, a result which accords with the more variable performance of the GBD subjects on this measure. However, the default pattern is stable for 50% of cases in the survey, surprisingly high for such a complex, emergent effect. The ranking of geminate error types is also somewhat less robust, being stable for 68% of the parameter sets in the full survey, although this rises to 92% for the less extreme parameter variation.
of the narrow survey. Performance remains relatively stable when we examine runs which show properties 1, 2, and 4 simultaneously, but the total falls considerably when the number of runs on which all five properties are shown is assessed. Evidently, error type ranking and geminate error pattern differ in the parameter sets which fail to preserve them. The entire error pattern is stable over 40% of the narrower survey.

In conclusion, we would claim that the major features of GBD are robust properties of the model under noise, and the more variable features in GBD patients’ performance, ranking of error types, and behaviour of geminated words, show a degree of parameter dependence in the model.

6. Discussion

We began by identifying six features of GBD spelling which we take to be central to the disorder: the effects of word length and serial position; the occurrence of five basic types of sequencing error; the occurrence of distinctive errors on doubled letters; the preservation of CV status, and qualitatively similar performance on words and non-words.

All of these features have been demonstrated by the model in the simulations reported above. The simulations show that the model also successfully matches a number of the finer-grained features of the disorder. At this more detailed level some limitations become apparent in the match between model and patients, however. We begin by summarising both the successes and limitations of the model, and in particular we consider whether the limitations suggest problems with the underlying theoretical approach or whether they result from simplifications or implementational details specific to the present version of the model. In the remainder of this section we suggest ways in which the model might be developed in future work, and then discuss the relationship of the model to established ideas about the cognitive mechanisms of spelling and to other models of spelling processes.

6.1. Successes

1. Effect of word length on recall. Study 1 demonstrates a qualitative fit to usual GBD performance and a good fit between the model and patient AS for words of up to eight letters.

2. Effect of serial position on error incidence. Study 2 demonstrates that the serial error incidence curves, both overall and for individual error types, are of similar shape to those produced by patients.

3. Proportions of errors of different types. Study 2 shows that the model is capable of showing features of the relative incidence of errors of different types common to a number of GBD patients (although see limitation 2 below).

4. Performance on geminate words. Study 3 shows that relationships between performance on geminate and non-geminate words shown by different GBD patients can be achieved by the model under the control of a single parameter influencing the relative robustness of the geminate representation. Furthermore, the model captures at a coarse level the pattern of errors produced by GBD patients involving geminate features.

5. Effect of lexicality. GBD patients show qualitatively similar performance on a number of measures for both word and non-word stimuli. The model shows qualitatively similar performance under normal and high-noise conditions, and we have argued that the high-noise condition can be interpreted as greater vulnerability to disruption for non-word stimuli.

6. Preservation of CV status in errors. The inclusion of CV information allows the model to match the relative preservation of CV status in the errors of some GBD patients. The addition of this information is demonstrated to be of utility to the model. The simple availability of CV information also allowed an explanation to be given on the model for the observed difference in the strength of CV preservation between exchange and substitution errors.
7. Stability of error pattern. Effects 1, 2, 4, and 6 listed above are all robust in the face of parameter variation. Effect 3, the relative incidence of different error types, is less so, although it is stable across half of the parametric survey of study 6. This pattern is however variable between GBD patients.

6.2. Limitations

The following we take to be the major limitations of the model. In particular the first two limitations indicate that the factors which determine the relative incidence of different error types produced by GBD patients are not well captured by the model at this level of analysis. We discuss all four limitations further below.

1. Incorrect trends in relative incidence of different error types with word length. The model shows the opposite trends in incidence of deletion and substitution errors to those shown by a majority of GBD patients.

2. Low rate of insertion errors. The model produces very few insertion errors by comparison with GBD patients.

3. Linguistic effects in spelling errors. The current version of the model includes only the CQ spelling output mechanism. We have not addressed linguistic or other features which may affect the production of errors by biasing activation in the competitive queue, other than to demonstrate the general principle in the case of CV effects. We believe that other biases in spelling errors will operate in a similar way at the level of the final CQ output mechanism, and their incorporation in future versions of the model should not therefore invalidate the basic range of effects demonstrated in the current model.

4. Geminate mechanism. The particular mechanism we have implemented for the production of geminate features has difficulties with multiple geminates in the same word.

6.3. Implications of limitations and issues for future models

Our aim in this work has been to account for the major features of GBD within a framework which allows the mechanisms of spelling to be elaborated beyond the simple generation of letter sequences. A number of simplifying assumptions have inevitably been made in the present model, but it is important to consider if the limitations listed above imply problems with the underlying theoretical approach or simply reflect the fact that the basic framework has yet to be fully fleshed out. We here discuss these issues under two headings—those which relate to the basic modes of error in the sequencing system, and those relating to further refinement of the mechanisms behind letter node activation.

6.4. Error mechanisms

Limitations 1 and 2 above indicate that the explanations provided by the model for the different error types in GBD may not be correct, or may not be complete. The mechanisms behind the relative incidences of different types of error in a CQ system are non-linear and far from trivial. Moreover, spelling is a complex skill and we should not expect to be able to model all aspects of the GBD error pattern simply from the perspective of a damaged serial ordering mechanism—other parts of the spelling system must surely be involved in some errors, and no doubt strategic factors play a part (Glasspool et al., 1995). It is thus difficult to know how far we should be prepared to push the basic mechanism to address detailed GBD data on its own. Nonetheless, it is possible to make some suggestions regarding specific error types.

The most basic mode in which insertion and deletion errors occur in a CQ system involves a cascade of letter movement errors following an initial erroneous response. Each letter in this cascade region involves a cascade of letter movements, which may mask the initial insertion or deletion. The propensity for letters to “move” in one direction rather than another is influenced by the model’s dynamics. However, the two types of error involve movement in opposite directions. The “gain control” parameter in the current model—see Appendix A, Eq. (5)—tends to favor movement towards the start of the word, and hence deletions rather than insertions. An additional problem is that the cascade region is more than normally susceptible to further errors (since no letter appears in its target position) which may mask the initial insertion or deletion. These problems suggest that the cascade of errors may not be an appropriate model for insertions and deletions in GBD spelling.

There exist plausible alternative mechanisms for both types of error that could be explored in future models. Deletions may be the result of an activation threshold that must be exceeded before a response can be made (an approach which is taken in some CQ models, e.g., Page & Norris, 1998). A related mechanism can also be suggested for insertion errors: two letters may be produced within a single time-step if they are very close together in activation. A competitive filter with limited power to separate nodes with close activations might produce such behaviour.

It is possible to test these suggestions without making major changes to the model. Table 6 shows the effect of word length on error proportions for a version of the model with two modifications: (1) An activation threshold of 0.6 must be exceeded by the winning letter node for output to be generated. (2) If the winning letter
exceeds its closest competitor in activation by less than 0.01, both are output on the same time-step and both are subsequently inhibited. All parameters are as listed in Appendix A (Table 7) apart from the “gain control” parameter \((g)\) which is 0, and the noise level which is adjusted to 0.55 to maintain a level of performance comparable with the previous simulations.

The modified model produces many more insertions, and for shorter words it shows the correct trend in deletions and substitutions. For longer words the trends are reversed, however. A large proportion of insertions occurs for shorter words, a trend which agrees with patient AS. Clearly these modifications alone will not fully address the issue. However, the example does demonstrate that trends in the error pattern are affected by the introduction of thresholds on letter production. We conclude that the apparently incorrect result at this level of detail need not rule out the general CQ approach, although further work will be required to elucidate the implications for the sequencing system of such trends in GBD patient data.

### 6.5. The incorporation of linguistic constraints

With respect to limitation 3 above, a major aim of this work was to demonstrate the incorporation of “soft” serial categorical constraints into the CQ sequencing paradigm. Study 5 shows that biasing the output competition with a CV template leads to preservation of CV status in errors (and that the additional complexity required to implement external constraints has a payoff in reducing the error rate). As with GBD patients the preservation of CV status is not absolute and the degree of preservation may be varied by adjusting the level of CV bias.

We have not committed ourselves to a particular source for this CV information. The overall framework we have introduced should allow different mechanisms for activating letter nodes to be straightforwardly incorporated, and as any CV bias present in such mechanisms would exert its influence through the biasing of letter node activations in the competitive queue, we would not anticipate that such refinements would materially affect the basic behaviour of the model. Different sources for a CV bias might however result in subtly different patterns in errors and might thus lead to interesting predictions concerning more detailed aspects of the errors produced by normal and agraphic spellers. Any mechanism which tends to bias the activation of a class of responses at certain points during sequence production should lead to soft serial constraints, so in principle any regularity in the processes which activate letter nodes could lead to corresponding regularities in spelling errors without affecting the gross effects of word length and serial position seen in the basic model.

The two features of the CQ approach which allow such regularities to be expressed smoothly in this way are activation-based sequencing, and a lack of associative response chaining. The representation of sequential position by activation level allows activation biases to influence sequence order directly, and the competitive selection of responses under noise means that even small biases can subtly influence error rates. The lack of chaining also allows biases to have a direct and simple effect on performance. Simple response chaining models predict that following an error, further errors will occur, because the current response contributes to cueing later responses. Thus, an isolated class-preserving exchange error, such as cinema \(\rightarrow\) cimena, with the rest of the word correct (including the intervening vowel), would not be expected to occur. (Properly speaking, it is the combination of a gradient-based competitive output process with refractory post-production inhibition which appears to be required to explain such errors. This does not in fact preclude chaining as the mechanism by which an activation gradient is established over a set of items, providing the final output is then produced by a CQ-like mechanism. Such hybrid mechanisms have yet to be properly investigated.) The addition of response biasing should increase the differences between CQ and chaining models in this regard. Categorical response biasing increases the likelihood of “long-distance” shift errors, i.e., ones in which the incorrectly produced response has moved some distance from its target position. In CQ models this does not differentially affect the likelihood of error at subsequent locations.

A class of process which is likely to produce regularities in a rather different way is that of deliberate spelling strategies. That strategic factors are important in spelling is clear (see Glasspool et al., 1995). Thus, people may develop idiosyncratic mnemonics or use rules (such

---

**Table 6**

Effect of word length on error proportions for a modified version of the model with activation thresholds for deletions and insertion errors

<table>
<thead>
<tr>
<th>Word length</th>
<th>Insertions</th>
<th>Deletions</th>
<th>Exchanges</th>
<th>Shifts</th>
<th>Substitutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 letters</td>
<td>43.2</td>
<td>2.3</td>
<td>4.5</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>4 letters</td>
<td>23.3</td>
<td>17.1</td>
<td>10.8</td>
<td>0.3</td>
<td>48.4</td>
</tr>
<tr>
<td>6 letters</td>
<td>17.4</td>
<td>13</td>
<td>17.6</td>
<td>1</td>
<td>50.8</td>
</tr>
<tr>
<td>8 letters</td>
<td>15.6</td>
<td>5.7</td>
<td>19.8</td>
<td>2.3</td>
<td>56.4</td>
</tr>
</tbody>
</table>

Figures shown are percentages of single-error responses.
as “I before E except after C”) to spell problematic words, and strategic processes of repair, possibly using phonological information, may come into action following a spelling slip. To an extent processes such as spelling by analogy may also come under this heading. Such processes are not within the remit of the current model, and may indeed be difficult to incorporate cleanly into any model of limited scope.

With respect to limitation 4 above, while the need for a separate mechanism to represent the doubling of a letter is a clear prediction of the CQ approach, the detailed operation of such a mechanism is an open issue. We have attempted to implement a theoretically neutral form of geminate mechanism in the current work, but clearly the mechanism we have used is over simplistic, for example, double geminates are not possible. Alternative, more complex and capable mechanisms could be directly substituted without changing the basic operation of the model. However, while it is clear that geminate status should be represented in the spelling model there is too little data as yet to fully constrain a decision about what types of process might be responsible for using this representation to produce geminated output. A number of open questions remain such as the degree to which GBD patients’ geminate errors take account of conventions of the target language (for example in English the doublets “kk” and “aa” are uncommon). Our aim has been to keep the present model theoretically neutral on such points so that more adequate approaches to geminate generation may be investigated from within the current framework.

6.6. Relationship to other models

Experimental studies of spelling have produced fewer attempts at modelling than the related problem of reading. Two examples of neural network spelling models are Brown and Loosemore (1994), and Olson and Caramazza (1994). Both are 3-layer connectionist sound-spelling conversion models trained on real English the doublets “kk” and “aa” are uncommon). Our aim has been to keep the present model theoretically neutral on such points so that more adequate approaches to geminate generation may be investigated from within the current framework.

The Brown and Loosemore model produces a purely spatial pattern of output (over a distributed letter representation) and hence does not address serial ordering processes. The Olson and Caramazza model generates serial activation of letters by providing serial phonological input, which, during training, is temporarily aligned with a target spelling pattern (the model is a kind of inverse of the Sejnowski & Rosenberg, 1987, NETtalk reading model). When a phonological input is (serially) presented to the trained network it produces a serial pattern of activation over letter nodes. Olson and Caramazza present results from artificial lesions of the model which cause it to produce more regularisation errors, however, no results of the type discussed above are reported, and the GBD pattern is not discussed. We would argue that the error pattern shown by the current model crucially depends on the operation of a competitive queue. As no such mechanism is present in the Olson and Caramazza model we would not expect it to be able to account for the typical errors of GBD. It is possible however to add a competitive output mechanism to a 3-layer network model. This is discussed in relation to a model of spelling by Glasspool (1998) and Glasspool et al. (1999). The resultant competitive sequencing process leads to an error pattern qualitatively similar to GBD for essentially the same reasons as in the current model.

The alternative model which has been applied most directly to GBD data is the multiple object spelling (MOS) model of Caramazza and colleagues (Caramazza & Miceli, 1990; Tainturier & Caramazza, 1996). Regarding the issue of representation there are some important similarities between this model and the present one. The MOS model proposes multi-dimensional graphemic representations in the graphemic buffer, with separate “tiers” corresponding to different classes of structural information. The orthographic representation of a word is held to comprise a set of ordered letter identity tokens, each bound with a C or V token corresponding to the letter’s CV status, and optionally bound with a geminate token indicating that the associated letter should be doubled. The letter tokens are organised by bindings to higher level elements identified as “graphosyllables”—hypothetical orthographic equivalents to phonological syllables. It is suggested that when letter tokens move about, due to graphemic buffer disruption, they preferentially come to rest at locations in the buffer having the appropriate CV label.

The aim of the MOS model is to codify the data which must be represented by the spelling system, not to propose a process by which letter sequences are to be generated from such representations. This information can help inform the questions posed in the previous section. The representational scheme shares several features with the representation of spellings in the current CQ model, and to the extent that the internal representations specified by each coincide the two models might be viewed as descriptions at different functional levels of the same underlying system. There are however some differences between the representational assumptions of the two approaches, one of which we believe to be of particular interest: the MOS model assumes a structural buffer with labelled slots, whereas the CQ approach sees serial behaviour as constructed on-line. The absence of any such rigid structure, and the fact that serial order has to be dynamically reconstructed, allows the CQ model to explain why order information
should be subject to disruption as well as allowing detailed explanations for error patterns to be explored. Based on the performance to date of models of the CQ type we believe this alternative notion of a “buffer” (discussed further below) will prove to be an essential feature in modelling many types of low-level serial behaviour.

6.7. Relationship to normal spelling

In this paper, we have considered the performance of the model in matching the disrupted spelling of GBD patients. However, an important point of the modelling effort is to gain insights into the operation of the spelling system in its undamaged state. The basic principles on which the current model is based were developed independently of the GBD data pattern and clearly must be applicable to normal spelling. That such models can explain error data in fluent touch typing was shown by Rumelhart and Norman (1982). With respect to handwriting, Wing and Baddeley (1980) looked at spelling errors produced by 40 students taking entrance examinations to Cambridge colleges, and analysed those errors they considered to be “slips,” i.e., not due to simply not knowing how the word should be spelled. The error types characteristic of GBD (omissions, substitutions, etc.) were all found (at a much lower rate, of course). In addition length and serial position effects were found, with errors being more likely in medial positions. These data suggest that the “pattern of vulnerability” in normal, skilled, spelling is similar to that found in GBD subjects, which supports the position that the errors of GBD patients are due to the degraded operation of the normal spelling system, rather than, for instance, interference from other processes. There are however some differences. GBD patients tend to make more exchange errors and fewer deletions, relatively, than normal spellers, and the preservation of CV status seen in some GBD patients has not yet been observed in slips of the pen.

However, the CQ framework implies some general constraints on sequence generation which have implications for any mode of behaviour which uses it. Two features of CQ in particular merit discussion:

Capacity. Under CQ, the more items which need to be encoded in a sequence, the more susceptible to disruption recall becomes, because successive items have to be stored “more closely” in the weight space (i.e., their relative positional indices, as realised by the weights, become more similar to each other). This leads to increased parallel access and competition at recall. In practice the approach is therefore limited in the length of sequence it can support in the face of disruptive noise. The prediction is therefore that longer words will have to be broken up into shorter chunks. In a similar model of speech production, Hartley and Houghton (1996) have suggested a mechanism whereby polysyllabic words can be “chunked” into smaller units, and a similar approach might be applicable in spelling longer words. However, in phonology the identity and status of sub-word chunks—syllables—is well established, whereas such ideas are currently more speculative in spelling. If chunking occurs, the usual mechanisms responsible for primacy and recency effects should operate within chunks, resulting in increased vulnerability to error for letters in the middle of each chunk (i.e., a series of inverted U error curves).

Repetition. The “select and inhibit” dynamics of CQ work against perseverative behaviour. This is particularly the case for doubled items which require special treatment. However, it is generally true of the CQ approach that there are processes at work which make any repeated items more difficult to generate within the framework. The inhibition and slow recovery of sequence items following production suggests a prima facie prediction that non-immediate repeats will facilitate errors, and more specifically that errors will tend to involve the second occurrence of an item, when its representation is still refractory following the first occurrence. Ward and Romani (1998), for example, conclude that words with repeated letters (e.g., fence) should be more error-prone than words with no repeats (e.g., lance) on any model of the CQ type. However, in practice the effect may be counteracted by a number of complimentary influences, depending on the details of a particular model. First, in conjunction with a dynamically changing timing signal (as with the I–E node signal of the current model) it is possible to achieve robust sequencing with a relatively rapid recovery from inhibition on the part of output items, which limits the extent of the effect. Second, the lower number of distinct letters in a word with repeats may tend to mask any increase in vulnerability to error. Third, a repeated item, in most types of CQ model, receives excitation more than once during sequence production and the repeated bursts of excitation can have an additive effect which gives an advantage to the repeated item. Finally, a number of implemented CQ models (although not the present one) learn to produce sequences during repeated exposure; such models automatically compensate for the effect of suppression by increasing the level of excitation given to the second occurrence of a repeated item in response to errors during learning. These effects are dependent to some extent on the details of implementation of a particular model and it is not clear whether they will in general fully counteract the natural vulnerability of a repeated item. For example, in the present model, when the second letter in a six-letter word is repeated in the fourth letter position, the second occurrence is approximately 10% more likely to suffer an error compared with the same position in a word without repeats. However, the first occurrence of the repeated letter is somewhat more robust then its
non-repeated counterpart. These effects critically depend on parameter selection and it is difficult to make a general prediction.

The issue has not generally been examined in empirical data, and where it has been reported the results are conflicting. For example Hotopf (1980) reports a vulnerability of the second occurrence of a repeated letter in “slips of the pen” of normal spellers. However, Ward and Romani (1998) do not find a clear effect in a dysgraphic patient.

6.8. A graphemic buffer?

Finally, we consider what the CQ approach has to say about the notion of a graphemic buffer itself. In “box-and-arrow” models the term “buffer” is used to describe devices performing two similar but distinct functions: (1) a short-term storage device which allows information to be passed between two systems which operate at different times or at different rates, or (2) a device which allows information to be assembled in a piecemeal fashion and in arbitrary order and then read out as a single consistent sequence.

When the CQ approach is used, as here, to model sequential output from long-term memory, its function does not appear to be well characterised by either of these meanings. Sequential output is generated on-line by the interactions between competing and inhibited items. The “buffer” does not contain a representation of a sequence which could be moved to or stored in another part of the system, because the sequence representation does not exist independently of the sequence generator. The term “buffer” does not seem appropriate for such a mechanism if it is viewed purely as performing a serial output generation task.

More importantly, it is not clear that a CQ system could easily be loaded with information in a piecemeal manner, which makes it unlikely that a CQ system could perform the function implied by the second meaning of “buffer.” This may impact on the usual assumptions about serial buffers which underlie box-and-arrow theories of dual routes in the spelling system (e.g., Morton, 1980; Seymour & Porpodas, 1980). As discussed above, our assumption in the current model has been that the assembled spelling is transferred to the CQ output stage. One rationale for this process is the presumed higher rate of operation of the assembled route than the pace of spoken output (Glasspool et al., 1995). In this mode of operation the CQ system would be acting as a buffer in the former sense, that of an interface between two systems operating at different rates.

We suggested that the transfer to the “buffer” could be effected by the rapid temporary learning of a serial output from the assembled route. While this may be a workable suggestion it does seem rather unwieldy. On the present model the required weight values are a relatively straightforward function of the target letter sequence; there is no interaction between representations of different words, and repeated exposure to a training corpus is not required. It may therefore be possible to implement a simple mechanism equivalent to the direct setting of these weights by the assembled route, for example by altering the responsiveness of a set of intermediate nodes. Such work is clearly beyond the scope of the current model. An alternative possibility, discussed by Glasspool (1998) and Glasspool et al. (1999), involves a generalisation of the CQ approach to a multi-layer network architecture which learns to map from distributed internal representations to sequential output. Such an approach may enable an assembled route to be directly incorporated into a CQ framework, the phonology-to-orthography mappings being learned by repeated exposure. Until these possibilities have been followed up with more extensive modelling, however, it is difficult to assess how complex the interaction between multiple routes may be in a model with a CQ output stage.

An interesting feature of the model, therefore, is that it contains nothing corresponding to the usual idea of the “graphemic output buffer” itself; some aspects of buffer-like behaviour (serial readout, temporary storage) are features of a process applied to representations already assumed to exist in structural accounts of the spelling system. The notion of a buffer in the sense of a storage component which can be loaded piecemeal and read out serially does not exist in the present model.

7. Conclusions

A full understanding of complex error patterns in neuropsychological deficits must include detailed consideration of the processes underlying normal performance, as well as the modular structure of the brain systems involved and the type and form of information represented in those systems. Understanding detailed patterns of data from specific domains such as spelling requires quantitative computational simulation of the dynamic processes involved; however computational models based on data from only one specific area can reduce to curve fitting. This can be avoided if the theoretical principles behind the simulation have independent support and can be used to make theoretical bridges between different bodies of work. In this paper, we have applied a general framework for modelling serial behaviour to spelling. This has permitted the simulation of a number of well-documented effects in a particular syndrome, graphemic buffer disorder. The model proposes that that the basic mechanisms underlying the representation and control of spelling are quite general ones, and that understanding of spelling, and spelling disorders, will be advanced by further investigation of mechanisms.
sometimes considered too “low-level” to form a significant part of traditional cognitive approaches.

Acknowledgments

We would like to thank Tim Shallice for numerous useful discussions about this work. We are also most grateful to Richard Cooper, Gordon Brown, Mike Page, Alfonso Caramazza, and several anonymous reviewers for their comments on previous versions of this paper. This work was supported by a grant from the McDonnel-Pew program in cognitive neuroscience.

Appendix A. Formal description

A.1. Item node activation

Item nodes are activated by the interaction of the Initiate–End (I–E) node activation vector with the learned weights in the sequence node to item node pathway. A radial basis activation function is implemented as an exponential function of the Euclidean distance between the I–E vector and the weight vector to any unit. The net input to an item node is the I–E vector and the weight vector to any unit. The exponential function of the Euclidean distance between the input and weight vectors is asymptotically implemented as an I–E node activation vector with the learned weight from item node to letter node

\[
A_i(t) = \begin{cases} 
(1 - gA_i(t-1))net_i^L & \text{if } A_i(t-1) \geq 0, \\
(1 + gA_i(t-1))net_i^L + rA_i(t-1) & \text{otherwise},
\end{cases}
\]

where \( r \) is a parameter which governs the rate of recovery from inhibition, and \( g \) is a small parameter \((0 < g < 1)\) which controls the degree of gain control (and thus asymmetry in the function, see Glasspool, 1998).

A.3. Competitive filter

The competitive filter nodes receive one-to-one excitatory input from letter nodes. There are two additional sources of activation: the activation levels of either consonants or vowels are all increased by a fixed amount depending on the current state of the CV template, and random noise is added to make the process of selecting the most active node prone to error. Initial activation of a filter node is thus given by:

\[
A_i^F = A_i^L + CV_i + \nu,
\]

where \( CV_i \) is the CV template input to the node, and \( \nu \) is the noise. In the current implementation the filter is simulated. The most active filter node is assumed to be the winner, and the corresponding letter node is subsequently set to a standard negative (inhibited) value (determined by the parameter \( \text{Inh} \)).

A.4. CV template

The model assumes that information regarding the C/V status of each target letter is available. Glasspool (1998) demonstrates one possible concrete example of a suitable mechanism for the template However, no theoretical weight is claimed for the implementation of this element and in the current work the template is assumed to be external to the model.

A.5. Representation of geminate letters

The same basic formulae are used for net input and activation of the geminate node as for the letter nodes. The net input to the geminate node is given by

\[
\text{net}^G = \sum_i A_i^j W_{iG},
\]

where \( W_{iG} \) is the weight from letter node \( i \) to the geminate node (these weights are all set appropriately to either 1 or 0 during learning). The activation of the geminate node at time \( t \) is
\[ A^G(t) = \begin{cases} \text{net}^G + v & \text{if } A^G(t-1) \geq 0, \\ \text{net}^G + rA^G(t-1) + v & \text{otherwise,} \end{cases} \tag{8} \]

where \( r \) is the same recovery rate parameter as that used for letter nodes, and \( v \) is the same random noise value used in Eq. (6). During spelling, the geminate node is held to have triggered if its activation exceeds a threshold \( T_G \). Following successful triggering the geminate node is inhibited in the same way as letter nodes.

### A.6. Learning and production

Sequences are learned by first setting the sequence-to-item weights, and then binding each item node to a letter node. The target sequence is presented to the model letter by letter, each input simultaneously activating, to a value of 1.0, a letter node, an item node representing the individual event or token, and optionally the geminate node. During presentation of the letter sequence, the I- and E-nodes obey Eqs. (9) and (10), respectively:

\[ A_I(t) = \delta^I, \tag{9} \]

\[ A_E(t) = \delta^{S-I}, \tag{10} \]

where \( A_I(t) \) and \( A_E(t) \), respectively, denote the activation of the I and E nodes at time \( t \), \( I \) is the number of letters in the word, and \( \delta \) is a parameter which sets the rate of change of the timing signal. \((t \geq 0 \text{ and } 0 < \delta_1 < 1)\). Eq. (10) requires that the length of the word be known in advance. This allows symmetrical activation functions to be used for the two nodes, whereas alternative activation functions which do not have this requirement (see Houghton, 1990) lead to asymmetric activation profiles. Symmetry between Initiate- and End-node activation functions leads to a more central peak in the serial error curve (see Study 2 above) which fits the spelling data well, as opposed to verbal STM and the structure of short-term memory. Journal of Verbal Learning and Verbal Behaviour, 14, 575–589.


### Table 7

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decay rate for I- and E-nodes</td>
<td>( \delta )</td>
<td>0.8</td>
</tr>
<tr>
<td>Slope of item activation function</td>
<td>( c )</td>
<td>4.0</td>
</tr>
<tr>
<td>Letter node gain control</td>
<td>( g )</td>
<td>0.6</td>
</tr>
<tr>
<td>Letter node recovery rate</td>
<td>( r )</td>
<td>0.7</td>
</tr>
<tr>
<td>Letter node inhibition level</td>
<td>( Inh )</td>
<td>−1.0</td>
</tr>
<tr>
<td>Geminate node trigger threshold</td>
<td>( T_G )</td>
<td>0.8</td>
</tr>
<tr>
<td>Stop threshold</td>
<td>( T_S )</td>
<td>0.2</td>
</tr>
<tr>
<td>C/V template activation bias</td>
<td>( B_{CV} )</td>
<td>0.2</td>
</tr>
<tr>
<td>Noise magnitude</td>
<td>( \nu )</td>
<td>±0.422</td>
</tr>
</tbody>
</table>

The competitive filter generates an output by selecting the most active of the competing responses, and the corresponding letter node is then inhibited. A stopping threshold \( T_S \) is applied to the activations of the letter nodes. When no letter node activation exceeds \( T_S \), the spelling operation stops.

Table 7 summarises the default parameter values that were used in all simulations unless otherwise stated.

### References


