Computer Assessment and Diagnostic Classification of Chronic Pain Patients

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ABSTRACT

Objective. In order to establish a diagnosis of chronic pain, emphasis is placed on a patient's report of the pain's intensity, location, and character. The aim of this study was to evaluate the feasibility of a computer assessment method to collect self-reports of pain that were then used in discriminant analyses to distinguish among chronic pain diagnoses.

Methods. A convenience sample of 511 patients from two university-based pain clinics completed a computer pain assessment battery that elicited demographic information, pain drawings, pain and emotion intensity ratings, and intensity ratings of verbal descriptors. Patients classified themselves into one of six chronic pain diagnoses. Discriminant analyses were performed in an attempt to identify the unique features of patients' pain experience associated with each of the diagnostic categories.

Results. Pain drawings successfully classified patients into three of the diagnostic categories (back, head, and neck pain). In a second analysis, two pain descriptors (cramping and stabbing) separated rheumatoid arthritis patients from those with either fibromyalgia or neural pain. One descriptor of pain (cramping) and one descriptor of emotion (frustration) together distinguished between fibromyalgia and neural pain.

Conclusions. 1) Computer assessment of a range of patient symptoms is feasible in the pain clinic. 2) Discriminant analysis based on pain drawings can distinguish among patient-reported diagnoses of back pain, headache, and neck pain. 3) Discriminant analysis based on three verbal descriptors can help to distinguish among diagnoses of fibromyalgia, neuralgia, and rheumatoid arthritis. 4) However, in general, most computerized descriptive information is not useful in distinguishing differences among pain patient diagnostic groups.

Key Words. Chronic Pain; Computer Assessment; Pain Diagnoses; Discriminant Analysis

Introduction

This article concerns two aspects of clinical pain management: computer assessment based on patient self-reports, and statistical analysis to distinguish among pain diagnoses.

Pain Assessment

According to a 1997 report of the American Academy of Pain Medicine and the American Pain Society, the prevalence of untreated moderate to severe pain is as high as 25%. One of the most daunting problems in attempting to ameliorate pain is its subjectivity. Pain is the primary symptom that prompts individuals to seek medical attention [1], but its subjective nature makes it difficult to measure [2]. According to Craig et al. [3], “Pain is a private experience with complex
sensory, affective, and evaluative qualities that must be measured if people in distress are to be helped” (p. 257). This broad definition acknowledges that the assessment of pain involves more than simply asking someone “how much does it hurt,” but rather, considers an array of psychological factors.

Because “pain” refers to an individual’s subjective experience, any description of the properties of pain can be reported with authority only by the person experiencing it, and therefore, self-report instruments are required. In the spirit of “evidence-based” medical practice, it is critical that health professionals be provided with a standardized means for determining the intensity, location, and character of pain, as well as its emotional impact on the patient.

With the dramatic and ongoing improvement in computer software and technology, our ability to satisfy clinical requirements of pain assessment has greatly improved. For example, touch screen data acquisition has become commonplace in outpatient offices. In their article on electronic subject diaries in clinical trials, Raymond and Ross [4] list the advantages for electronic data acquisition as compared with paper-and-pencil administration. These include 1) direct transfer from a user’s computer device to a central database; 2) no necessity for staff to enter data, actively manage the database, or clean the data; and 3) the ability of a dynamic display to permit a variety of user-friendly and visually meaningful data entry elements and formats. We would add to this list the ability to use graphical formats possible only with the computer, and the ability to perform statistical analyses of group data quickly to identify patterns of response to assist in the assignment of pain diagnoses [5,6]. In light of these technological developments, there is potential clinical value for computer methods that collect and analyze symptom reports of patients in chronic pain.

**Pain Diagnosis**

In the field of pain medicine, there is often a scarcity of physical examination findings to help make a diagnosis; thus, great emphasis is placed on patient self-report. Both bodily pain locations and verbal descriptors selected by patients to describe their pain are thought to be extremely important in distinguishing among diagnoses. In the clinic, however, the relative weight and perceived usefulness of different types of assessment data are largely left up to the discretion of the attending pain specialist. There appear to be no agreed-upon standards that are consistently applied across clinics, or for that matter, within the same clinic by different individuals.

A number of studies have attempted to establish some standardization by using statistical routines for classifying patients based on self-reports. For example, studies have examined the ability of the verbal descriptors of the McGill Pain Questionnaire to assist in the discrimination among conditions [7–12]. Dubuisson and Melzack [7] correctly classified 77% of their cases into eight clinical pain syndromes through discriminant analysis of verbal descriptors, and were able to improve their predictions when pain drawings on a silhouette of the human body were included. Melzack et al. [8] also reported the usefulness of the McGill Pain Questionnaire in discriminating between trigeminal neuralgia and atypical facial pain. Based on this work and that by others, it appears that certain patterns of symptom descriptions can be successfully diagnosed relying on patient self-reports, which serve as input to a computer classification method [11–14].

The present study was conducted in the spirit of these pioneer research efforts, but with greater emphasis on the computer for both collecting and analyzing symptom reports. Our aims were two-fold: to evaluate the feasibility of a computer assessment of pain based on patient self-reports, and to determine if such data could be used in discriminant analyses to distinguish among pain diagnoses.

**Methods**

**Participants**

The study was conducted in the pain management clinics at two university-based medical centers (Dartmouth-Hitchcock Medical Center and Brigham & Women’s Hospital) and was approved by their respective Committees for the Protection of Human Subjects. Participants were patients who entered the pain management centers for treatment. Patients were asked to complete a brief computer survey involving ratings of their pain. The chief inclusion criterion was a self-reported diagnosis of low back pain, headache, neck pain, fibromyalgia, neuralgia (nerve pain), or rheumatoid arthritis. Additional inclusion criteria were self-reported pain during the previous 6 months, the ability to understand English, and the ability to use the computer to complete the assessment measures. Excluded were individuals under the age of 18, and those with a mental or physical disabili-
ity (e.g., poor eyesight, inability to manipulate a computer mouse) that precluded their understanding or performance of the task. Each participant received a check or gift certificate of $25 for completing the assessment battery.

Procedure

Computer Language and Platforms

The program for the computer assessment of pain was written in True Basic for a stand-alone application and was implemented on a Dell laptop computer with a 15-inch screen. A data management program read the data for each patient and created an aggregate file that could be analyzed by SPSS v. 11.5 (SPSS Inc., Chicago, IL).

Demographic Information

At the beginning of each test session, patients signed an informed consent form, and the research assistant entered the following demographic information: identification number (consecutive in order of participation), diagnosis (low back, neck, headache, fibromyalgia, neuralgia, rheumatoid arthritis), gender, age, marital status (single, married, separated, divorced, widowed), ethnic/racial background (White, African American, Hispanic/Latino, Asian, Native American, Other), education (in years), employment status (full-time, part-time, not working), compensation status (receiving benefits, not receiving benefits), duration of current pain problem (years, months), and number of pain-related surgeries. All recording and storage of demographic data complied with the regulations of the Health Insurance Portability and Accountability Act (HIPAA). Following the entry of this information, the participant completed the assessment battery.

Computer Assessment of Pain

Each participant completed three assessment modules that have been described in previous work [15,16]. The program asks patients: 1) to adjust the length of bars along a visual analog scale to indicate pain intensity and the emotional impact of pain; 2) to mark the locations of pain on an outline diagram of the human body; and 3) to rate the salience of 11 pain descriptors and 11 emotion descriptors. Practice trials were first conducted for each module of the program to familiarize the user with the displays and the manner of entering ratings.

Visual Analog Scale: Pain and Emotion Intensity

A visual analog scale appeared on the screen in a horizontal orientation. The scale did not contain any tick marks or numbers, because we learned during pilot investigations that some patients chose a number first and then made the bar equal the number, thus defeating the purpose of the continuous scale. The length of the scale was 14 cm. The labels along the scale were None, Mild, Moderate, and Severe. The phrase “typical pain in the last two weeks” appeared immediately above the scale for ratings of pain, and the phrase “typical emotional distress in the last two weeks” appeared in the same place for ratings of emotional impact. At the top of the screen for rating pain intensity, the patient was instructed to “Indicate the intensity of your pain,” and for the rating of emotion, “Indicate the emotional impact of your pain.” Patients made ratings by adjusting a horizontal green bar (1 cm in width) whose length was changed by clicking, holding, and moving the mouse. An illustration of the display is shown in Figure 1. The adjustment process continued until the patient was satisfied with the rating.

Pain Drawings

Outline drawings of the human body were shown on the computer monitor. The patient’s task was to point the cursor at a painful location on the drawings and click. Marked locations were designated by small red squares superimposed over the drawings. The drawings consisted of left and right views of the human head (two figures) and front and back views of the body. Patients could mark entire regions of the figure by depressing the mouse and “painting” with it. Figure 2 shows the pain locations (red squares) marked on the body by one of the patients.

Descriptor Words

The list of words describing pain and, in a separate list, emotional impact appeared in a column at the left margin of the screen. The 11 pain descriptors were: splitting, tender, heavy, aching, hot-burning, gnawing, cramping, sharp, stabbing, shooting, and throbbing. The 11 emotion descriptors were: sickness, fear, exhaustion, depression, anxiety, frustration, anger, stress, sadness, disgust, and shame [15].

The response options for each word appeared along the top of the display with numbers associated with each option. For pain descriptors the sentence “My pain felt like it was . . .” appeared at the top of the screen. The response options were: Not This (0), Mild (1), Moderate (2), and Severe (3). For emotion descriptors, the relevant sentence was “My pain made me feel . . .,” and the response
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options were: Not This (0), Mildly (1), Moderately (2), and Severely (3). The spacing between the four numbers representing the response options was equal. The patients were instructed to indicate how each word described their pain/emotion over the last 2 weeks. In previous work we showed that this judgment is closely linked to the modal (usual) single rating of pain during the time period of interest [17]. Patients selected a response by pointing and clicking on one of the numerical response options. Each click circled the number associated with the option in red. Patients were allowed to change their minds about a response by pointing and clicking on another option. It was necessary for the patient to give some response for each descriptor. If a descriptor was not assigned a response and the patient attempted to continue with the assessment, a sentence appeared asking the patient to complete the rating for the particular descriptors that had not yet been rated. An example of the computer display is shown in Figure 3.

Results

In all cases, statistical significance was taken as a probability value less than 0.05 (two-tailed test).

Diagnoses

Out of a total of 511 patients, the frequencies in the six diagnostic categories were: low back pain (N = 259), rheumatoid arthritis (N = 71), headache (N = 63), neck pain (N = 46), neuralgia (N = 38), and fibromyalgia (N = 34).

Demographics

Summary results for the categorical demographic variables are presented in Table 1, along with the results of \( \chi^2 \) tests and significance levels for comparisons among the response options within each category. The patients were predominantly female (65%), married (58%), and white (87%). Almost two-thirds of the patients were unemployed (64%) and the other third (32%) were receiving disability benefits. All differences among diagnostic categories were significant except ethnicity.

Table 2 presents descriptive statistics (means and standard deviations) for the continuous demographic variables. Statistical differences among the six diagnostic categories were tested by one-way ANOVAs using each of the four variables in Table 2. The \( F \) values and \( P \) values are given in the table. Significant differences were found among the six diagnoses for Age, Education, Duration of Pain, and Number of Surgeries. Those patients with rheumatoid arthritis tended to be older, have more years of education, have had more surgeries, and

![Figure 1](#) Emotional impact on a typical day over the last 2 weeks.

![Figure 2](#) Pain locations marked (in red) by one research participant on a standardized computer display of a drawing of the human body.

![Figure 3](#) Eleven pain descriptors on a computer display with the range of response options.
have been in pain longer than the other groups. Those patients with headaches tended to be younger but also tended to have been in pain for a longer period of time. The results of most of the post hoc comparisons among pairs of diagnoses were not significant.

**Intensity and Descriptor Ratings**

Table 3 presents means and standard deviations of ratings for intensity, emotional impact, the average rating of the 11 pain descriptors, and the average rating of the 11 emotion descriptors. These measures are presented for each of the six diagnoses. Differences among diagnostic categories were tested by one-way ANOVAs for each of the four variables in Table 3. Each test yielded significant differences among the diagnoses (Intensity: $F = 8.2$, $P < 0.001$; Emotional Impact: $F = 3.7$, $P < 0.001$; mean Pain Descriptor $F = 6.5$, $P < 0.001$; and mean Emotion Descriptor rating: $F = 6.5$, $P < 0.001$). It is clear that important differences exist among patient self-reports of pain depending on the diagnostic category. Post hoc comparisons indicated that patients with rheumatoid arthritis showed the greatest differences in comparison with the other diagnoses. The next question we addressed was whether or not a computer classification method could take these

### Table 1: Summary of demographic variables for six diagnostic groups (N = 511)

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Gender (% Female)</th>
<th>Marital (% Married)</th>
<th>Ethnicity (% White)</th>
<th>Employment (% Not Work)</th>
<th>Compensation (% Benefits)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Back</td>
<td>53</td>
<td>59</td>
<td>86</td>
<td>68</td>
<td>36</td>
</tr>
<tr>
<td>Head</td>
<td>81</td>
<td>56</td>
<td>92</td>
<td>43</td>
<td>17</td>
</tr>
<tr>
<td>Neck</td>
<td>71</td>
<td>41</td>
<td>71</td>
<td>76</td>
<td>47</td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>82</td>
<td>68</td>
<td>95</td>
<td>68</td>
<td>34</td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>80</td>
<td>59</td>
<td>92</td>
<td>72</td>
<td>18</td>
</tr>
<tr>
<td>Neuralgia</td>
<td>74</td>
<td>52</td>
<td>91</td>
<td>46</td>
<td>35</td>
</tr>
<tr>
<td>Total</td>
<td>65</td>
<td>58</td>
<td>87</td>
<td>64</td>
<td>32</td>
</tr>
</tbody>
</table>

$\chi^2$ = 37.8, $\chi^2 = 33.1$, $\chi^2 = 31.6$, $\chi^2 = 47.7$, $\chi^2 = 17.9$, $\chi^2 = 0.001$, $\chi^2 = 0.03$, $\chi^2 = 0.17$, $\chi^2 = 0.001$, $\chi^2 = 0.003$.

### Table 2: Demographic differences among diagnostic groups (N = 511)

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Age Mean (SD)</th>
<th>Education in Years Mean (SD)</th>
<th>Duration of Pain (Years) Mean (SD)</th>
<th>No. of Surgeries for Pain Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Back</td>
<td>53.7 (14.9)</td>
<td>13.1 (2.5)</td>
<td>7.4 (9.3)</td>
<td>1.3 (3.3)</td>
</tr>
<tr>
<td>Head</td>
<td>43.0 (11.5)</td>
<td>14.1 (3.8)</td>
<td>16.2 (14.0)</td>
<td>0.2 (0.8)</td>
</tr>
<tr>
<td>Neck</td>
<td>50.0 (9.6)</td>
<td>13.5 (2.2)</td>
<td>5.7 (7.4)</td>
<td>0.6 (1.5)</td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>61.2 (12.9)</td>
<td>15.7 (13.1)</td>
<td>15.7 (14.0)</td>
<td>2.0 (4.2)</td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>48.2 (13.1)</td>
<td>13.1 (3.1)</td>
<td>8.6 (7.3)</td>
<td>1.3 (2.0)</td>
</tr>
<tr>
<td>Neuralgia</td>
<td>49.5 (11.4)</td>
<td>13.3 (2.6)</td>
<td>4.1 (3.8)</td>
<td>1.9 (5.1)</td>
</tr>
<tr>
<td>Total</td>
<td>52.4 (14.3)</td>
<td>13.6 (5.5)</td>
<td>9.3 (11.0)</td>
<td>1.3 (3.2)</td>
</tr>
</tbody>
</table>

$F = 14.0$, $F = 2.6$, $F = 16.4$, $F = 2.7$, $F = 0.001$, $F = 0.02$.

### Table 3: Intensity and descriptor ratings differences among diagnostic groups (N = 511)

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Pain Intensity* Mean (SD)</th>
<th>Emotion Intensity* Mean (SD)</th>
<th>Pain Descriptors† Mean (SD)</th>
<th>Emotion Descriptors† Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Back</td>
<td>77.4 (17.9)</td>
<td>60.2 (29.3)</td>
<td>1.4 (0.7)</td>
<td>1.4 (0.8)</td>
</tr>
<tr>
<td>Head</td>
<td>70.8 (25.7)</td>
<td>64.6 (24.8)</td>
<td>1.5 (0.6)</td>
<td>1.6 (0.7)</td>
</tr>
<tr>
<td>Neck</td>
<td>76.3 (19.2)</td>
<td>68.8 (25.6)</td>
<td>1.4 (0.6)</td>
<td>1.4 (0.7)</td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>61.8</td>
<td>54.8 (29.9)</td>
<td>1.1 (0.6)</td>
<td>1.2 (0.8)</td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>80.7 (14.7)</td>
<td>74.2 (23.8)</td>
<td>1.8 (0.7)</td>
<td>1.7 (0.7)</td>
</tr>
<tr>
<td>Neuralgia</td>
<td>79.3 (15.8)</td>
<td>69.3 (22.3)</td>
<td>1.5 (0.7)</td>
<td>1.7 (0.7)</td>
</tr>
<tr>
<td>Total</td>
<td>74.7 (20.9)</td>
<td>62.4 (28.1)</td>
<td>1.4 (0.7)</td>
<td>1.4 (0.8)</td>
</tr>
</tbody>
</table>

* 0–100 scale.
† 0–3 scale (mean intensity of 11 descriptors).
patient self-reports and place individuals into their diagnostic categories.

**Discriminant Analysis**

Separate analyses were conducted to determine how well different measures predicted patient membership in the diagnostic categories. Predictors included the continuous demographic variables, the intensity variables, and the two sets of descriptor words (pain and emotion words). In addition, we conducted a discriminant analysis based on the proportion of the area that a patient marked within each of 15 nonoverlapping regions on the pain diagram. These regions were designated as: head, neck, chest, abdomen, pelvic, shoulder, upper arm, lower arm, upper back, lower back, buttocks, upper leg, lower leg, foot, and hand. The regions chosen were slight modifications of those originally defined by Margolis et al. [18]. No distinctions were made between different views of the same body parts. For example, the “upper leg” region included both legs viewed from both the front and back. Each analysis was conducted without weighting the diagnostic categories by the number of cases. We report a step-wise procedure, although it did not yield results very different from entering all variables at the same time.

The degree of success in classifying patients into the appropriate diagnostic category is summarized in Table 4. Except for the analysis based on pain location (69.7% success), the rates of correct classification are low, ranging from 22.9% correct when using the four intensity variables to 36% when using the four continuous demographic variables.

Table 4 also shows details of how well the discriminant analyses predicted membership in each of the diagnostic categories. The analysis based on pain location is satisfactory with regard to the diagnoses of back, headache, and neck. With the possible exception of headache, the analyses based on the other variables are not very successful at classifying patients into their diagnostic categories.

Although discriminant analysis is not very successful in categorizing patients into these six diagnoses based on ratings of descriptor words, the method may be more effective with a smaller set of diagnoses. As noted earlier, the analysis based on results from the pain diagram has fairly good success in identifying patients suffering from back, head, or neck pain. We then conducted an analysis of the three remaining diagnoses, which are sometimes difficult to distinguish based on clinical examination: fibromyalgia, neuralgia, and rheumatoid arthritis. Using the step-wise discriminant method and the 11 pain descriptors as variables, the analysis correctly predicted group membership for 70% of the patients with rheumatoid arthritis, 53% of the patients with fibromyalgia, and 53% of the patients with neuralgia. Only two descriptors, stabbing and cramping, were found to separate the rheumatoid arthritis patients from those in the other two categories. Patients with rheumatoid arthritis indicated more cramping, whereas those with fibromyalgia and neuralgia indicated more stabbing pain.

We then added the 11 emotion descriptors and attempted to distinguish between neuralgia and fibromyalgia. This analysis was successful in identifying 79% of the patients with fibromyalgia and 68% of the patients with neuralgia. The only two descriptors that entered into this analysis (out of a total of 22) were cramping and frustration. The patients with neuralgia weighted heavily on frustration, whereas the patients with fibromyalgia weighted heavily on cramping. These results indicate that only three descriptor words (stabbing, cramping, and frustration) differentiate among the diagnoses of rheumatoid arthritis, fibromyalgia, and neuralgia.

It is worth noting that the value of particular descriptors depends on the specific diagnoses being considered. For example, that a descriptor does not discriminate between one set of

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Percent of cases appropriately classified by discriminant analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis</td>
<td>Demographics</td>
</tr>
<tr>
<td>Back</td>
<td>28.2</td>
</tr>
<tr>
<td>Head</td>
<td>55.6</td>
</tr>
<tr>
<td>Neck</td>
<td>50.0</td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>52.1</td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>20.6</td>
</tr>
<tr>
<td>Neuralgia</td>
<td>23.7</td>
</tr>
<tr>
<td>All diagnoses</td>
<td>36.0</td>
</tr>
</tbody>
</table>
diagnoses does not mean it will be ineffective when used with a smaller subset of these diagnoses. The sequential process of conducting a series of discriminant analyses is summarized in Table 5. The overriding result is that the vast majority of descriptors were not effective in distinguishing among the six diagnoses considered here.

**Discussion**

The computer assessment of pain is a viable approach to collecting self-report data from patients in a clinical setting. In the present study only one person refused to participate because it involved the computer, and only 3% of those participating required help from the research assistant in entering data. These latter individuals would have the same kinds of trouble completing standard paper-and-pencil questionnaires.

In this study we were able to distinguish among three diagnoses (low back pain, headache, and neck pain) out of six based on the location of pain marked by patients on outlines of the human body. Other analyses involving patient demographics, intensity ratings of pain, and verbal descriptors were not very successful in separating patients into the appropriate diagnostic categories. Previous research, on the other hand, suggests that intensity ratings can be used to distinguish between more specific painful conditions. For example, Hunter [19] used discriminant analysis using intensity ratings to correctly classify 71% of headache patients into the appropriate subgroup (tension vs migraine headache).

Our results also do not agree with past work on the ability of verbal descriptors to discriminate between common painful conditions. In our study, many patients chose the same words with the same frequency regardless of clinical diagnosis. Dubuisson and Melzack [7] were able to correctly classify 77% of patients by using verbal descriptors, and based on such results, they suggested that each type of clinical pain syndrome was characterized by a specific set of descriptors. After they added data on sex, age, spatial location of pain, and analgesic drugs to their discriminant analysis, 100% of their patients were correctly classified into 20 appropriate diagnostic categories. They do not provide specifics, however, on how these data were collected or exactly which quantitative measures were used (e.g., for pain location). In our study, individuals with a self-reported diagnosis of headache were the only patients appropriately classified with some degree of consistency. When we examined the discriminant analysis based only on the 11 emotion descriptors, the results for all six diagnoses looked similar. The same was true for five of the six diagnoses with the 11 pain descriptors; the exception being headache, where the descriptor “splitting” separated these patients from the other groups. Eighty-four percent of headache patients chose this word, but it is unclear whether this result merely reflects what most people stereotypically associate with headaches, or in fact represents a true description of the painful experience. A majority of our patients from all diagnostic categories selected “angry” as one of the emotion descriptors. In agreement with our findings, Wade et al. [20] found that “anger” and “frustration” are frequent concomitants in reports by chronic pain patients.

One possible explanation for our inability to correctly classify many pain patients based on most of the descriptive words is that we did not use the right words; for example, we did not include “tingling” or “numbness.” The literature on neuropathic pain, in particular, suggests that these words are key clinical predictors [11,21–23]. Earlier research has shown that patients with acute pain syndromes show less differentiation between verbal descriptors, making it difficult to determine the etiology of an acute injury [24]. Differences have been demonstrated in the types of words chosen by acute vs chronic pain patients [25]. Atkinson et al. [26] suggested that chronic pain patients, especially those with affective disorders, may not use pain descriptors in a system-

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Pain Diagram</th>
<th>Pain Descriptors</th>
<th>Pain &amp; Emotion Descriptors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Back</td>
<td>78.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head</td>
<td>88.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neck</td>
<td>76.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rheumatoid arthritis</td>
<td>49.3</td>
<td>70.4 (cramping)*</td>
<td></td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>47.1</td>
<td>52.9 (stabbing)*</td>
<td>79.4 (cramping)*</td>
</tr>
<tr>
<td>Neuralgia</td>
<td>28.9</td>
<td>52.6 (stabbing)*</td>
<td>68.4 (frustration)*</td>
</tr>
</tbody>
</table>

* Descriptor mainly associated with a diagnosis.
atic way. Such confusion on the part of patients could make it difficult for an analysis to discriminate between conditions based solely on verbal descriptors.

Our results corroborate previous findings that verbal descriptors are not helpful in discriminating among chronic pain conditions. When Atkinson et al. [26] examined patients with chronic pain (daily pain for greater than six months), they were unable to demonstrate a discriminative ability for the verbal descriptors in the McGill Pain Questionnaire [27]. Three separate discriminant analyses were performed. In the first experiment, a discriminant analysis was performed using patients categorized as having benign pain, cancer pain, or renal pain. In the second discriminant analysis the patients in the three main groups were divided into 14 chronic pain categories. In the final discriminant analysis patients were included only if their pain intensity was less than or equal to 50 on a zero-to-100 scale, where zero was no pain and 100 was pain as bad as it could be. None of these analyses correctly classified patients into the appropriate diagnostic categories. They concluded, much as we do, that pain syndromes with different etiologies are not associated with unique patterns of verbal descriptors by patients.

In a meta-analysis of 51 studies, Wilkie et al. did not find distinct patterns of word selection for clinical pain syndromes [28]. Jamison et al. [15] also found that healthy controls and chronic pain patients choose similar words when asked either to report on their pain (patients) or to imagine they are in pain (healthy subjects). It appears that although some investigators find unique links between verbal descriptors and particular pain diagnoses, others (including us) find that most verbal descriptors commonly used in clinical settings are of little help in establishing diagnoses for patients with chronic pain.

Apart from the inadequacies of discriminant analysis in this field, there are some tangible benefits to the use of a computer assessment of pain. Here we were able to analyze a large amount of descriptive data and the pain locations identified on the pain diagram by the number of pixels used in each site. This type of analysis would have been difficult and extremely time-consuming if we had collected assessment data using paper forms. Despite the benefits, no differences are suspected between what would have been reported using a computer and using a paper questionnaire. It is unknown if other electronic diary programs using different items would be more useful in identifying diagnostic groups of pain patients. Also it is not known how computerized descriptive information could be used by clinicians in accurately determining treatment strategies. Current studies are pursuing this line of research by investigating the role of electronic pain diaries in pain centers.

Several limitations of this study deserve mention. First, the diagnoses were based on patient report rather than on the opinion of the attending pain specialist. Although the patients had all been experiencing chronic pain and had been notified of their diagnosis by a clinical specialist before participating in this study, it is uncertain how reliable this information was. Although patients were restricted to choosing only one primary diagnosis, we know that chronic pain patients frequently report multiple pain sites. Also, we purposely limited this study to patients with only one of six diagnoses, because they are the types of patients most frequently treated in pain centers. Inclusion of patients with other diagnoses or evaluation of patients with multiple diagnoses may have shown other results.

Second, there was a statistical limitation of the present work due to the small sample sizes used in some of the discriminant analyses. Most the patients (50%) had low back pain as their primary diagnosis. The limited numbers with other diagnoses made it less feasible to check the validity of the analyses. In the future, it would be desirable to replicate or extend this study with larger sample sizes in each of the diagnostic categories. Finally, this study is based on information obtained during one session. Repeated data collection over time may help to improve the identification of differences among pain patient groups.

Conclusion

We have demonstrated that a computer assessment method is feasible within the context of a pain management center treating patients with a variety of demographic characteristics and who present with a variety of chronic pain syndromes. The use of computer methods to collect self-reports from these patients makes it easier to analyze group data to identify response patterns that might be uniquely associated with different diagnoses.

In the present study we used discriminant analysis to categorize patients as belonging to one of six diagnostic groups, using a sequential procedure in which the first analysis was based on pain drawings, and subsequent analyses were based on pain
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and emotion descriptors. The complete group of 22 verbal descriptors was a relatively poor classifier of patients into chronic pain categories, but a subset (three descriptors) was able to distinguish among three similar diagnoses (rheumatoid arthritis, fibromyalgia, and neuralgia).

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