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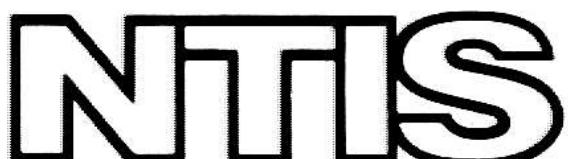
INDUCTIVE METHODS FOR PROVING  
PROPERTIES OF PROGRAMS

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BY

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INDUCTIVE METHODS FOR PROVING  
PROPERTIES OF PROGRAMS\*

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Zohar Manna  
Stephen Ness  
Jean Vuillemin

**ABSTRACT:** We have two main purposes in this paper. First, we clarify and extend known results about computation of recursive programs, emphasizing the difference between the theoretical and practical approaches. Secondly, we present and examine various known methods for proving properties of recursive programs. We discuss in detail two powerful inductive methods, computational induction and structural induction, illustrating their applications by various examples. We also briefly discuss some other related methods.

Our aim in this work is to introduce inductive methods to as wide a class of readers as possible and to demonstrate their power as practical techniques. We ask the forgiveness of our more theoretical-minded colleagues for our occasional choice of clarity over precision.

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# INDUCTIVE METHODS FOR PROVING PROPERTIES OF PROGRAMS

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## Abstract

We have two main purposes in this paper. First, we clarify and extend known results about computation of recursive programs, emphasizing the difference between the theoretical and practical approaches. Secondly, we present and examine various known methods for proving properties of recursive programs. We discuss in detail two powerful inductive methods, computational induction and structural induction, illustrating their applications by various examples. We also briefly discuss some other related methods.

Our aim in this work is to introduce inductive methods to as wide a class of readers as possible and to demonstrate their power as practical techniques. We ask the forgiveness of our more theoretical-minded colleagues for our occasional choice of clarity over precision.

## Introduction

Many different inductive methods have been used to prove properties of programs. Well-known methods include for example recursion induction, structural induction, inductive assertions, computational induction, truncation induction, and fixedpoint induction. Our intention in this paper is to present and examine these methods, illustrating their application for proving properties of recursive programs.

In Section I we give the theoretical background necessary to understand the fixedpoint approach to recursive programs (essentially following Scott [1969, 1970]), as well as the practical computational approach. We emphasize that while existing inductive methods prove properties of the 'least fixedpoint function' of a recursive program, in practice the function computed by some common computation rules differs from it. We briefly suggest 'fixedpoint' computation rules which assure that the computed function is identical to the least fixedpoint.

In Section II we examine computational induction methods, i.e., methods in which the induction is based on the steps of the computation. We first present the extremely simple induction method introduced by Scott (deBakker and Scott [1969], Scott [1969]). Examples are presented which introduce various applications of the method. We also discuss another computational induction method, truncation induction (Morris [1971]). A related method, called fixedpoint induction, is described in Park [1970].

We describe the structural induction method and its application for proving properties of programs in Section III. This method was suggested explicitly by Burstall [1969], although it was often used previously, for example by McCarthy and Painter [1967] for proving the correctness of a compiler and by Floyd [1967] for proving termination of flowchart programs. Our intention in this section is to emphasize, by means of appro-

priately chosen examples, that the choice of a suitable partial ordering on the data structure and a suitable induction hypothesis leads to simple and clear inductive proofs. Although we show that computational induction and structural induction are essentially equivalent, there are practical reasons for keeping both of them in mind. Computational induction is best suited for proving the correctness and equivalence of programs, and because of its simplicity it is particularly convenient for machine implementation (Milner [1972a, 1972b]). On the other hand, termination of programs is usually easier to show by structural induction.

In Section IV, we introduce two additional methods: recursion induction (McCarthy [1963b]), which was actually the first method proposed for proving properties of recursive programs, and inductive assertions (introduced by Floyd [1967] and Naur [1966] for flowchart programs and generalized by Manna and Pnueli [1970] for recursive programs). We show that any proof by these methods can be effectively translated to a proof by computational induction.

## I. RECURSIVE PROGRAMS

In this section, we introduce a theory of partial functions, and show its relation to recursive programs and their computations.

### Partial Functions

We wish to consider partial functions from a domain  $D_1$  into a range  $D_2$ , i.e., functions which may be undefined for some arguments. For example, the quotient function  $x/y$ , mapping  $\mathbb{R} \times \mathbb{R}$  (pairs of real numbers) into  $\mathbb{R}$ , is usually considered to have no value if  $y = 0$ . Partial functions arise naturally in connection with computation, as a computing process may give results for some arguments and run indefinitely for others.

In developing a theory for handling partial functions it is convenient to introduce the special element  $\omega$  to represent the value undefined. We let  $D^*$  denote  $D \cup \{\omega\}$ , assuming  $\omega \notin D$  by convention; when  $D$  is the cartesian product  $A_1 \times \dots \times A_n$ , we let  $D^*$  be  $A_1^* \times \dots \times A_n^*$ .

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Any partial function  $f$  mapping  $D_1$  into  $D_2$  may then be considered as a total function mapping  $D_1$  into  $D_2^+$ : if  $f$  is undefined for  $d \in D_1$ , we let  $f(d)$  be  $\omega$ .

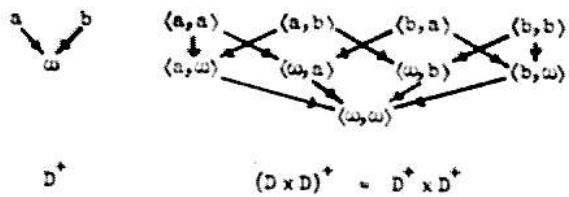
Since we shall consider compositions of partial functions, we may need to compute functions with some arguments being undefined. Thus we must extend every function mapping  $D_1$  into  $D_2^+$  to a function mapping  $D_1^+$  into  $D_2^+$ ; such extensions are discussed in the next section. Partial predicates are of course a special case, since a partial predicate is a partial function into {true, false}.

#### The Ordering $\leq$ on the Domain

To define appropriate extensions of partial functions from  $D_1$  into  $D_2$  to total functions from  $D_1^+$  into  $D_2^+$ , we first introduce the partial ordering  $\leq$  on every extended domain  $D^+$ . The partial ordering  $\leq$  is intended to correspond to the notion 'is less defined than', and accordingly we define it by letting  $\omega \leq d$  for all  $d \in D^+$ . Note that distinct elements of  $D$  are unrelated by  $\leq$ : for distinct  $a$  and  $b$  in  $D$ , neither  $a \leq b$  nor  $b \leq a$  holds. If  $D^+$  is the cartesian product  $A_1^* \times \dots \times A_n^*$ , we define  $(a_1, \dots, a_n) \leq (b_1, \dots, b_n)$  when  $a_i \leq b_i$  for each  $i$ ,  $1 \leq i \leq n$ .

Example. If  $D = \{a, b\}$ , then  $D^+ = \{a, b, \omega\}$  and  $(D \times D)^+ = \{(\omega, \omega), (\omega, a), (\omega, b), (a, \omega), (a, a), (a, b), (b, \omega), (b, a), (b, b)\}$ . The partial orderings on  $D^+$  and  $(D \times D)^+$  are described in the diagrams below, where each connecting line indicates that the lower element is less defined than the upper element. (Lines implied by transitivity or reflexivity are not shown.)  $\square$

✓ A partial ordering is a binary relation which is reflexive  $((\forall a)(a \leq a))$ , antisymmetric  $((\forall a, b)[a \leq b \wedge b \leq a \Rightarrow a \text{ is identical to } b])$ , and transitive  $((\forall a, b, c)[a \leq b \wedge b \leq c \Rightarrow a \leq c])$ . As usual, we write  $a \subset b$  if  $a \leq b$  and  $a$  is not identical to  $b$ ,  $a \not\leq b$  if  $a \leq b$  does not hold, etc.



#### Monotonic Functions

Any function  $f$  computed by a program has the property that whenever the input  $x$  is less defined than the input  $y$ , the output  $f(x)$  is less defined than  $f(y)$ . We therefore require that the extended function  $f$  from  $D_1^+$  into  $D_2^+$  be monotonic, i.e.,

$$x \leq y \text{ implies } f(x) \leq f(y).$$

We let  $(D_1^+ \rightarrow D_2^+)$  denote the set of all monotonic functions from  $D_1^+$  into  $D_2^+$ .

If  $f$  has only one argument, monotonicity requires that  $f(\omega)$  be  $\omega$ , with one exception: the constant function  $f(x) = c$  for all  $x \in D^+$ . If  $f$  has many arguments, i.e.,  $D_1 = A_1 \times \dots \times A_n$ , it may have many different monotonic extensions. A particularly important extension of any function is called the natural extension, defined by letting  $f(d_1, \dots, d_n)$  be  $\omega$  whenever at least one of the  $d_i$  is  $\omega$ . This corresponds intuitively to the functions computed by programs which must know all their inputs before beginning execution (e.g., Algol call by value).

Examples. (a) The identity function, mapping any  $x$  in  $D^+$  into itself, is obviously monotonic.

(b) The quotient function, mapping  $(x, y)$  into  $x/y$ , extended to a total function by letting  $x/0$  be  $\omega$  for any  $x$  in  $R$ , becomes monotonic by the natural extension: let  $x/\omega$  and  $\omega/y$  be  $\omega$  for any  $x$  and  $y$  in  $R^+$ .

(c) The equality predicate mapping  $D \times D$  into {true, false} can be extended in the following particularly interesting ways:

(i) The natural extension (weak equality), denoted by  $\sim$ , yields the value  $\omega$  whenever at least one of its arguments is  $\omega$ . The weak equality predicate is of course monotonic.

✓ We assume all the functions of our examples to be naturally extended, unless otherwise noted.

(ii) Another extension (strong equality), denoted by  $\equiv$ , yields the value true when both arguments are  $\omega$  and false when exactly one argument is  $\omega$ ; in other words,  $x \equiv y$  if and only if  $x \leq y$  and  $y \leq x$ . The strong equality predicate is not a monotonic mapping from  $D^+ \times D^+$  into  $\{\text{true}, \text{false}, \omega\}$ , since  $(\omega, d) \leq (d, d)$  but  $(\omega \equiv d) \not\leq (d \equiv d)$  (i.e., false  $\not\leq$  true) for  $d \in D$ .

(d) The if-then-else function, mapping  $\{\text{true}, \text{false}\} \times D \times D$  into  $D$ , is defined for any  $a, b \in D$  by letting

the value of  $(\text{if true then } a \text{ else } b)$  be  $a$ , and

the value of  $(\text{if false then } a \text{ else } b)$  be  $b$ .

It can be extended to a monotonic function mapping  $\{\text{true}, \text{false}\}^* \times D^+ \times D^+$  into  $D^+$  by letting, for any  $a, b \in D^+$ ,

the value of  $(\text{if true then } a \text{ else } \omega)$  be  $a$ ,  
the value of  $(\text{if false then } \omega \text{ else } b)$  be  $b$ , and

the value of  $(\text{if } \omega \text{ then } a \text{ else } b)$  be  $\omega$ .

Note that this is not the natural extension of if-then-else.  $\square$

#### Composition of Functions

An important operation on functions is composition, which allows functions to be defined in terms of simpler functions. If  $f$  is a function from  $D_1^+$  to  $D_2^+$  and  $g$  a function from  $D_2^+$  into  $D_3^+$ , then the composition of  $f$  and  $g$  is the function from  $D_1^+$  into  $D_3^+$  defined by  $g(f(x))$  for every  $x$  in  $D_1^+$ . It is easy to show that, if  $f$  and  $g$  are monotonic functions, so is their composition.

Examples. (a) The function  $f$ , given by  $f(x) = (\text{if } x = 0 \text{ then } 1 \text{ else } x)$ , is defined by composition of the weak equality predicate, the constant functions 0 and 1, the identity function, and the if-then-else function. Since all these functions are monotonic,  $f$  is monotonic.

(b) The function  $f$ , given by  $f(x) = (\text{if } x = \omega \text{ then } 0 \text{ else } 1)$ , defined using the nonmonotonic predicate  $\equiv$ , is not monotonic, since  $f(\omega) = 0$  and  $f(0) = 1$  (i.e.,  $\omega \leq 0$ , but  $f(\omega) \not\leq f(0)$ ).

(c) The functions  $f_1$  and  $f_2$ , given by

$$f_1(x) = g(\text{if } p(x) \text{ then } h_1(x) \text{ else } h_2(x))$$

and

$$f_2(x) = \text{if } p(x) \text{ then } g(h_1(x)) \text{ else } g(h_2(x)),$$

are defined by composition of if-then-else,  $p$ ,  $g$ ,  $h_1$  and  $h_2$ . If  $p$ ,  $g$ ,  $h_1$  and  $h_2$  are monotonic,  $f_1$  and  $f_2$  are monotonic. There is an interesting relation between these two functions:

(i)  $f_2(x) \leq f_1(x)$  for any  $x$  ; (ii) if

$g(\omega) = \omega$ , then  $f_2(x) = f_1(x)$  for any  $x$ . We shall use these results (and a similar result when  $g$  has several arguments) often in later proofs.  $\square$

#### The Ordering $\leq$ on Functions

Let  $f$  and  $g$  be two monotonic functions mapping  $D_1^+$  into  $D_2^+$ . We say that  $f \leq g$ , read " $f$  is less defined than  $g$ ", if  $f(x) \leq g(x)$  for any  $x$  in  $D_1^+$ ; this relation is indeed a partial ordering on  $(D_1^+ \rightarrow D_2^+)$ . Two functions  $f$  and  $g$  are equal,  $f = g$ , iff  $f \leq g$  and  $g \leq f$  (that is,  $f = g$  iff  $f(x) = g(x)$  for every  $x \in D_1^+$ ). We denote by  $\Omega$  the function which is always undefined:  $\Omega(x)$  is  $\omega$  for any  $x \in D_1^+$ . Note that  $\Omega \leq f$  for any function  $f$ .

Infinite increasing sequences

$f_0 \leq f_1 \leq f_2 \leq \dots$  of functions in  $(D_1^+ \rightarrow D_2^+)$  are called chains. It can be shown that any chain has a unique limit function in  $(D_1^+ \rightarrow D_2^+)$ , denoted by  $\lim_i f_i$ , which has the characteristic properties that  $f_i \leq \lim_i f_i$  for every  $i$ , and for any function  $g$  such that  $f_i \leq g$  for every  $i$ , we have  $\lim_i f_i \leq g$ .  $\square$

Example. Consider the sequence of functions  $f_0, f_1, \dots$  over the natural numbers defined by  $f_i(x) = (\text{if } x \leq i \text{ then } x! \text{ else } \omega)$ . This sequence is a chain, as  $f_i \leq f_{i+1}$  for every  $i$ ;  $\lim_i f_i$  is the factorial function.  $\square$

#### Continuous Functionals

We now consider a function  $\tau$  mapping the set of functions  $(D_1^+ \rightarrow D_2^+)$  into itself, called a functional; that is,  $\tau$  takes any monotonic function  $f$  as its argument and yields a monotonic function  $\tau[f]$  as its value. As for

functions, it is natural to restrict ourselves to monotonic functionals, i.e.,  $\tau$  such that  $f \leq g$  implies  $\tau[f] \leq \tau[g]$  for all  $f$  and  $g$  in  $(D_1^+ - D_2^+)$ . For our purposes, however, we require that functionals satisfy a stronger property, called continuity:  $\tau$  is continuous if for any chain of functions

$$f_0 \leq f_1 \leq f_2 \leq \dots$$

we have

$$\tau[f_0] \leq \tau[f_1] \leq \tau[f_2] \leq \dots$$

and

$$\tau[\lim_i f_i] = \lim_i \tau[f_i].$$

We usually specify a functional  $\tau$  by composition of known monotonic functions and the function variable  $F$ , denoted by  $\tau[F](x)$ ; when  $F$  is replaced by any known monotonic function  $g$ , the composition rules determine  $\tau[g](x)$ . It can easily be shown that any functional defined by composition of monotonic functions and the function variable  $F$  is continuous.

Examples. (a) The identity functional  $\tau_1$  defined by  $\tau_1[F](x) = F(x)$ , mapping any  $f$  in  $(D_1^+ - D_2^+)$  into itself, is clearly continuous.  
 (b) The constant functional  $\tau_g$  defined by  $\tau_g[F](x) = g(x)$ , mapping any  $f$  in  $(D_1^+ - D_2^+)$  into the function  $g$ , is continuous.  
 (c) The functional  $\tau$  defined by  $\tau[F](x) = (\text{if } x = 0 \text{ then } 1 \text{ else } F(x+1))$  is constructed by composition of monotonic functions (if-then-else, addition, weak equality, and the constant functions 0 and 1) and the function variable  $F$ ; it is therefore continuous. Given any monotonic function  $g$  over the integers,  $\tau[g]$  is another monotonic function over the integers:

if  $g = \Omega$ , then  $\tau[g](x) = (\text{if } x = 0 \text{ then } 1 \text{ else } \omega)$ ;  
 if  $g(x) = x-1$ , then  $\tau[g](x) = (\text{if } x=0 \text{ then } 1 \text{ else } x)$ .

(d) The functional  $\tau$  defined by  $\tau[F](x) = (\text{if } \forall x [F(x) = x] \text{ then } F(x) \text{ else } \omega)$  is monotonic but not continuous; if we consider the chain  $g_0 \leq g_1 \leq \dots$  where  $g_i(x) = (\text{if } x < i \text{ then } x \text{ else } \omega)$ ,  $\tau[g_i] = \Omega$  for any  $i$  so that  $\lim_i \tau[g_i] = \Omega$ , whereas  $\tau[\lim_i g_i]$  is the

identity function.  $\square$

### Fixedpoints

The fundamental property of a continuous functional  $\tau$  mapping  $(D_1^+ - D_2^+)$  into itself is that it has a unique least-fixedpoint  $F_\tau$ , having the two characteristic properties:  $F_\tau = \tau[F_\tau]$  and, for any  $g$ ,  $g = \tau[g]$  implies  $F_\tau \leq g$ .

We can compute  $F_\tau$  as the limit of the chain  $\Omega \leq \tau[\Omega] \leq \tau^2[\Omega] \leq \dots$  as follows from Kleene's first recursion theorem [1950].

Examples. All the functionals in the following examples are defined by composition of monotonic functions and the function variable  $F$  and are therefore continuous by construction and have unique least fixedpoints.

(a) The functional  $\tau$  over  $(N^+ - N^+)$ , given by

$$\tau[F](x) = (\text{if } x = 0 \text{ then } 1 \text{ else } F(x+1)),$$

has as fixedpoints the functions

$$s_n(x) = (\text{if } x = 0 \text{ then } 1 \text{ else } n)$$

for each  $n \in N^+$ .

The least fixedpoint is

$$F_\tau(x) = (\text{if } x = 0 \text{ then } 1 \text{ else } \omega).$$

(b) The only (and therefore least) fixedpoint of the functional  $\tau$  over the integers given by

$$\tau[F](x) = (\text{if } x > 100 \text{ then } x-10 \text{ else } F(x+1)),$$

$$\text{is } F_\tau(x) = (\text{if } x > 100 \text{ then } x-10 \text{ else } 91).$$

(c) The functional  $\tau$  over the integers, defined by

$$\tau[F](x_1, x_2) =$$

$$(\text{if } x_1 = x_2 \text{ then } x_2+1 \text{ else } F(x_1, F(x_1-1, x_2+1))),$$

has as fixedpoints the functions

$$f(x_1, x_2) = x_1+1,$$

$$g(x_1, x_2) = (\text{if } x_1 \geq x_2 \text{ then } x_1+1 \text{ else } x_2-1), \text{ and}$$

$$h(x_1, x_2) = (\text{if } (x_1 \geq x_2) \wedge (x_1 - x_2 \text{ even}) \text{ then } x_1+1 \text{ else } \omega),$$

the latter being the least fixedpoint  $F_\tau$  (Morris [1968]).  $\square$

We consider a functional  $\tau$  over  $(D_1^+ - D_2^+)^n$  to be given by coordinate functionals

$\tau_1, \dots, \tau_n$ , so that  $\tau[F_1, \dots, F_n]$  is  $(\tau_1[F_1, \dots, F_n], \dots, \tau_n[F_1, \dots, F_n])$ . It follows directly from the definition of the ordering on  $(D_1^+ - D_2^+)^n$  that  $\tau$  is continuous iff each  $\tau_i$  is continuous. A continuous functional  $\tau$  over  $(D_1^+ - D_2^+)^n$  has a unique least fixedpoint  $F_\tau = (F_{\tau_1}, \dots, F_{\tau_n})$ ; that is

- (a)  $F_{\tau_i} = \tau_i[F_{\tau_1}, \dots, F_{\tau_n}]$  for all  $i$ ,  $1 \leq i \leq n$ ;
- (b) For any fixedpoint  $g = (g_1, \dots, g_n)$  of  $\tau$ , i.e.,  $g_i = \tau_i[g_1, \dots, g_n]$  for all  $i$  ( $1 \leq i \leq n$ ),  $F_{\tau_i} \leq g_i$  for all  $i$  ( $1 \leq i \leq n$ ).

Example. Consider the functional  $\tau[F_1, F_2] = (\tau_1[F_1, F_2], \tau_2[F_1, F_2])$  over  $(\mathbb{N}^+ - \mathbb{N}^+)^2$ , where:

$$\tau_1[F_1, F_2](x) = (\text{if } x = 0 \text{ then } 1 \text{ else } F_1(x-1) + F_2(x-1))$$

and

$$\tau_2[F_1, F_2](x) = (\text{if } x = 0 \text{ then } 0 \text{ else } F_2(x-1)).$$

For any  $n \in \mathbb{N}^+$ , the pair  $(e_n, h_n)$  defined by

$$e_n(x) = (\text{if } x = 0 \vee x = 1 \text{ then } 1 \text{ else } (x-1) \cdot n + 1)$$

and

$$h_n(x) = (\text{if } x = 0 \text{ then } 0 \text{ else } n)$$

is a fixedpoint of  $\tau$ , since  $e_n = \tau_1(e_n, h_n)$  and  $h_n = \tau_2(e_n, h_n)$  (and therefore  $(e_n, h_n) = \tau[e_n, h_n]$ ). The least fixedpoint is the pair:

$$((\text{if } x = 0 \vee x = 1 \text{ then } 1 \text{ else } \omega),$$

$$(\text{if } x = 0 \text{ then } 0 \text{ else } \omega)).$$

□

### Recursive Programs

So far, we have been concerned only with functions considered abstractly, as purely mathematical objects. For example, we thought of the factorial function as a certain mapping between arguments and values, without considering how the mapping is specified. To continue our discussion we must introduce at this point a "programming language" for specifying functions. A function will be specified by a piece of code in the syntax of the language and then will be executed according to computation rules given by the semantics of

the language.

In the rest of this paper we use for illustration a particularly simple language, chosen because of its similarities to familiar languages such as ALGOL or LISP.<sup>\*/</sup> A program in our language, called a recursive definition or recursive program, is of the form

$$F(x) \leq \tau[F](x)$$

where  $\tau[F](x)$  is an expression representing composition of known monotonic functions and predicates and the function variable  $F$ , applied to the individual variable  $x$ .<sup>\*\*/</sup> For example, the following is a program for computing the factorial function:

$$F(x) \leq \text{if } x = 0 \text{ then } 1 \text{ else } x \cdot F(x-1).$$

This program resembles the ALGOL declaration

integer procedure  $f(x);$   
 $f := \text{if } x = 0 \text{ then } 1 \text{ else } x \cdot f(x-1);$

and the LISP definition

DEFINE ((  
 $(F \text{ (LAMBDA } (X) (\text{COND } ((\text{ZEROP } X) 1)$   
 $\text{ (T } (\text{TIMES } X \text{ (F } (\text{SUB1 } X))))))))).$

Of course our programs are meaningless until we describe the semantics of our language, i.e., how to compute the function defined by a program. The next step is therefore to give computation rules for executing programs. Our aim is to characterize the rules such that for every program  $F(x) \leq \tau[F](x)$  the computed function will be exactly the least fixedpoint  $F_\tau$ .

\*/ Although our programming language is very simple, it is powerful enough to express any "partial recursive" function, hence by Church's thesis any "computable" function (see, for example, Minsky [1967]).

\*\*/ We shall purposely be vague in our definitions in this section to avoid the introduction of the notion of schemas and interpretations. For a formal approach, see Nanna and Pnueli [1970] or Cadiou [1972].

### Computation Sequence

Let  $F(x) \leq \tau[F](x)$  be a program over some domain  $D^*$ . For a given input value  $d \in D^*$  (for  $x$ ), the program is executed by constructing a sequence of terms  $t_0, t_1, t_2, \dots$ , called a computation sequence for  $d$ , as follows:

- (1) The first term  $t_0$  is  $F(d)$ ;
- (2) For each  $i$ ,  $i \geq 0$ , the term  $t_{i+1}$  is obtained from  $t_i$  in two steps: first
  - (a) substitution: some occurrences of  $F$  (see below) in  $t_i$  are replaced by  $\tau[F]$  simultaneously; and then
  - (b) simplification: known functions and predicates are replaced by their values, whenever possible, until no further simplifications can be made;
- (3) The sequence is finite and  $t_n$  is the final term in the sequence if and only if no further substitution or simplification can be applied to  $t_n$  (that is, when  $t_n$  is an element of  $D^*$ ).

### Computation Rules

A computation rule  $C$  tells us which occurrences of  $F$  should be replaced by  $\tau[F]$  in each substitution step. For a given computation rule  $C$ , the program defines a partial function  $F_C$  mapping  $D^*$  into  $D^*$  as follows: If for input  $d \in D^*$  the computation sequence for  $d$  is finite, we say that  $F_C(d)$  is defined and  $F_C(d) = t_n$ ; if the computation sequence for  $d$  is infinite, we say that  $F_C(d) = \omega$ .

The following are examples of typical computation rules:

- (a) Kleene's computation rule: Replace all occurrences of  $F$  simultaneously. We denote the computed function by  $F_K$ .
- (b) leftmost-innermost rule: Replace only the leftmost-innermost occurrence of  $F$  (that is, the leftmost occurrence of  $F$  with all arguments free of  $F$ 's). We denote the computed function by  $F_{LI}$ . This is the rule which corresponds to the usual stack-implementation of recursion for languages like LISP or ALGOL. Any procedure evaluates all its arguments before execution.

- (c) leftmost outermost rule: Replace only the leftmost-outermost occurrence of  $F$ . We denote the computed function by  $F_{LO}$ .

Example 1. We consider the recursive definition of the "91-function" over the integers:

$F(x) \leq \text{if } x > 100 \text{ then } x-10 \text{ else } F(F(x+11))$ .

We illustrate the computation sequences for  $x = 99$  using the three rules.

- (a) Using Kleene's rule:

$t_0$  is  $F(99)$

if  $99 > 100$  then  $99-10$

else  $F(F(99+11))$  [substitution]

$t_1$  is  $F(F(110))$

[simplification]

if [if  $110 > 100$  then  $110-10$

else  $F(F(110+11))) > 100$

then [if  $110 > 100$  then  $110-10$

else  $F(F(110+11))) - 10$

else  $F(F([if  $110 > 100$  then  $110-10$$

else  $F(F(110+11))) + 11))$

[substitution]

$t_2$  is  $F(F(111))$

[simplification]

if [if  $111 > 100$  then  $111-10$

else  $F(F(111+11))) > 100$

then [if  $111 > 100$  then  $111-10$

else  $F(F(111+11))) - 10$

else  $F(F([if  $111 > 100$  then  $111-10$$

else  $F(F(111+11))) + 11))$

[substitution]

$t_3$  is 91.

[simplification]

In short, omitting simplifications and underlining the occurrences of  $F$  used for substitution:

$F(99) \rightarrow \underline{F(F(110))} \rightarrow \underline{F(F(111))} \rightarrow 91$ . Thus,

$F_K(99) = 91$ .

- (b) Using the leftmost-innermost rule:

$F(99) \rightarrow \underline{F(F(110))} \rightarrow \underline{F(100)} \rightarrow \underline{F(F(111))} \rightarrow \underline{F(101)} \rightarrow 91$ .

Thus,  $F_{LI}(99) = 91$ .

- (c) Using the leftmost-outermost rule:

$F(99) \rightarrow \underline{F(F(110))}$

$\rightarrow \underline{\text{if } F(110) > 100 \text{ then } F(110)-10 \text{ else } F(F(F(110)+11))}$

$\rightarrow \underline{F(F(F(110)+11))} \rightarrow \dots$

$\rightarrow \underline{\text{if } F(F(110)+11) > 100 \text{ then } F(F(110)+11)-10 \text{ else } \dots}$

$\neg F(110) \cdot 9 = 91$ .

Thus,  $F_{10}(99) = 91$ .  $\square$

An important property of  $F_C$  should be mentioned at this point (Cadiou [1972]):

For any computation rule  $C$ , the computed function  $F_C$  is less defined than the least fixepoint, i.e.,  $F_C \leq F_7$ , but they are not necessarily equal.

A program may consist in general of a system of recursive definitions of the form

$$\begin{cases} F_1(\bar{x}) \Leftarrow \tau_1[F_1, \dots, F_n](\bar{x}) \\ F_2(\bar{x}) \Leftarrow \tau_2[F_1, \dots, F_n](\bar{x}) \\ \vdots \\ F_n(\bar{x}) \Leftarrow \tau_n[F_1, \dots, F_n](\bar{x}) \end{cases},$$

where each  $\tau_i$  is an expression representing a composition of known monotonic functions and predicates and the function variables

$F_1, F_2, \dots, F_n$  applied to the individual variables  $\bar{x} = (x_1, \dots, x_n)$ . The generalization of the computation rules to systems of recursive definitions is straightforward; the computed function  $F_C$  of the system can be described as  $(F_{C_1}, F_{C_2}, \dots, F_{C_n})$ , where each  $F_{C_i}$  is computed as described above. The results of this section still hold for systems of recursive definitions.

#### Fixpoint Computation

All the methods for proving properties of programs described in the rest of this paper are based on the assumption that the computed function is equal to the least fixepoint. We are therefore interested only in the computation rules that yield the least fixepoint. We call such computation rules fixpoint computation rules.

Let  $\alpha[F^1, \dots, F^k](d)$  denote any term, where we use superscripts to distinguish the individual occurrences of  $F$  in  $\alpha$ . Suppose that we choose for substitution the occurrences  $F^1, \dots, F^i$  (for some  $i$ ,  $1 \leq i \leq k$ ) of  $F$  in  $\alpha$ . We say that this is a safe substitution if:

$$(\forall F^{i+1}, \dots, F^k) \alpha(\bar{a}, \dots, \bar{a}, F^{i+1}, \dots, F^k)(d) = \omega.$$

Intuitively, the substitution is safe if the values of  $F^{i+1}, \dots, F^k$  are not relevant: as long as  $F^1, \dots, F^i$  are not known, the value of

$\alpha[F^1, \dots, F^k](d)$  cannot be determined; hence, there is no need to compute  $F^{i+1}, \dots, F^k$  at this point.

A safe computation rule is any computation rule which uses only safe substitutions. It can be shown that any safe computation rule is a fixedpoint rule (Vuillemin [1972]). For example, since Kleene's rule and the leftmost-outermost rule are safe, they are both fixedpoint rules.

The leftmost-innermost rule, however, is not safe. The following example illustrates a program for which  $F_{LI} \neq F_7$ ; that is, the leftmost-innermost rule is not a fixedpoint rule.

Example 2. Consider the program over the integers

$$F(x, y) \Leftarrow \text{if } x = 0 \text{ then } 1 \text{ else } F(x-1, F(x-y, y)) .$$

The least fixepoint  $F_7$  is

$$F_7(x, y) = (\text{if } x \geq 0 \text{ then } 1 \text{ else } \omega) .$$

We compute  $F(1, 0)$  using the leftmost-innermost computation rule:

$$F(1, 0) \rightarrow F(0, F(1, 0) \rightarrow F(0, F(0, F(1, 0)))) \rightarrow \dots$$

and so on. The sequence is infinite, and therefore  $F_{LI}(1, 0) = \omega$ . In fact

$$F_{LI}(x, y) = (\text{if } x = 0 \vee (x > 0 \wedge y > 0 \wedge (y \text{ divides } x)) \text{ then } 1 \text{ else } \omega) ,$$

which is strictly less defined than  $F_7$ .

This example is closely related to an example of Morris [1968].  $\square$

In practice, the fixedpoint computation rules described so far (Kleene's rule and the leftmost-outermost rule) lead to very inefficient computations. In the rest of this section we describe and illustrate a fixedpoint computation rule, called the normal computation rule, which leads to efficient computations. In fact, since our computation rules do not allow the reuse of previously computed values of the program, the normal computation rule can be shown to perform the minimum possible number of substitutions (Vuillemin [1972]).

By this rule,  $t_{i+1}$  is obtained from  $t_i$  by substituting  $\tau[F]$  for one occurrence of  $F$  chosen as follows: we try first to replace the leftmost-outermost occurrence of  $F$  in  $t_i$  by  $\tau[F]$ , and start to evaluate the necessary tests in the new term, in order to eliminate the if-then-else connectives. If this is possible, we are done.

Otherwise, we choose a new occurrence of  $F$  in  $t_i$ , which corresponds to the first  $F$  we had to test during the previous evaluation, and repeat the process.

In other words, the idea is to delay the evaluation of the arguments of the function variables  $F$  as much as possible. This rule is quite close to Algol 60 "call by name" for procedures. However, there are two important differences: (a) absolutely no side effects are allowed, and (b) each argument of the procedures is evaluated at most once, namely the first time (if ever) it is needed.

We denote the computed function by  $F_N$ . The normal rule is safe, and it is therefore a fixed-point rule. The rule can be implemented in programming languages with almost no overhead, and provides an attractive alternative to call by value, which is not a fixedpoint rule, and call by name, which is not efficient.

Example 3. Consider the program over the natural numbers

```
F(x,y) <= if x = 0 then y+1
           else if y = 0 then F(x-1,1)
           else F(x-1,F(x,y-1)).
```

We shall compute  $F(2,1)$  using the normal computation rule. The occurrence of  $F$  chosen for substitution is underlined.

```
F(2,1) -> F(1,F(2,0)) -> F(1,F(1,1))
-> F(1,F(0,F(1,0))) -> F(1,F(1,0)+1)
-> F(1,F(0,1)+1) -> F(1,1) -> F(0,F(1,2))
-> F(1,2)+1 -> F(0,F(1,1))+1 -> F(1,1)+2
-> F(0,F(1,0))+2 -> F(1,0)+3 -> F(0,1)+3 -> 5 .
```

Note that in  $F(1,F(2,0))$ , for example, the inner occurrence of  $F$  was chosen for substitution, since trying to substitute for the outer  $F$  would lead to

```
if 1 = 0 then ...
else if F(2,0) = 0 then ...
else ... ,
```

which requires testing for the value of  $F(2,0)$ .

We compare below the number of substitutions required for each computation rule on this example.

Normal rule: 14

Kleene's rule: 23

Leftmost-innermost: 14

Leftmost-outermost: 10

$F_N(x,y) = F_T(x,y)$  is known as "Ackermann's function". This function is of special interest in recursive function theory because it grows faster than any primitive recursive function; for example,  $F_T(0,0) = 1$ ,  $F_T(1,1) = 5$ ,  $F_T(2,2) = 7$ ,  $F_T(3,3) = 61$ , and  $F_T(4,4) = 2^{2^{2^{2^{16}}}} - 3$ .

□

Example 4. Consider the program over the integers:

```
F(x,y) <= if x = 0 then 1 else F(x-1,F(x-y,y)) .
```

We shall compute  $F(2,1)$ , using the normal computation rule:

```
F(2,1) -> F(1,F(1,1))
```

```
-> F(0,F(1-F(1,1),F(1,1))) -> 1 .
```

We again compare the substitutions required:

Normal rule: 5

Kleene's rule: 7

Leftmost-innermost: 7

Leftmost-outermost: 5

## II. COMPUTATIONAL INDUCTION

The first method we shall describe is conceptually very simple: in order to prove some property of a program, we show that it is an invariant during the course of the computation.

For simplicity, we shall first explain the method for simple programs, consisting of a single recursive definition, then generalize to more complex programs.

### Computational Induction for a Single Recursive Definition

To prove the property  $P(F_\tau)$  of the function  $F_\tau$  defined by  $F \Leftarrow \tau[F]$ , it is sufficient to:

- Check that  $P$  is true before starting the computation, i.e.,  $P(\Omega)$ ; and
- Show that, if  $P$  is true at one step of the computation, it remains true after the next step, i.e.,  $P(F)$  implies  $P(\tau[F])$  for every  $F$ .

In short

from  $P(\Omega)$  and  $\forall F[P(F) \Rightarrow P(\tau[F])]$ , infer  $P(F_\tau)$ .

Since this rule is not valid for any  $P$ ,<sup>\*/</sup> we shall only consider admissible predicates<sup>\*\*/</sup>

<sup>\*/</sup> Consider, for example, the recursive definition over the natural numbers  $F(x) \Leftarrow \text{if } x = 0 \text{ then } 1 \text{ else } x \cdot F(x-1)$ , and the predicate  $P(\Omega) : \exists x[F(x) = \omega \wedge x \neq \omega]$ . Then  $P(\Omega)$  and  $\forall F[P(F) \Rightarrow P(\tau[F])]$  hold; since  $F_\tau(x)$  is a total function (the factorial function),  $P(F_\tau)$  does not hold.

<sup>\*\*/</sup> A class  $AP$  of admissible predicates can be defined as:

$$\begin{aligned} (AP) &= (AP) \wedge (AP) \mid \forall \bar{x}(EP) \\ (EP) &= (EP) \vee (EP) \mid Q(\bar{x}) \mid \alpha(F)(\bar{x}) \subseteq \beta(F)(\bar{x}) \end{aligned}$$

where  $Q(\bar{x})$  is any first order predicate, and  $\alpha$  and  $\beta$  are two continuous functionals.

$P(F)$  which are simply conjunctions of inequalities:  $\alpha(F) \subseteq \beta(F)$ , where  $\alpha$  and  $\beta$  are two continuous functionals.

In this case, the justification of the principle is easy: if  $\alpha(\Omega) \subseteq \beta(\Omega)$  and  $\forall F[\alpha(F) \subseteq \beta(F) \Rightarrow \alpha(\tau[F]) \subseteq \beta(\tau[F])]$ , then by a simple induction,  $\alpha(\tau^i(\Omega)) \subseteq \beta(\tau^i(\Omega))$  for every  $i \geq 0$ . Therefore, since  $\beta(\tau^i(\Omega)) \subseteq \beta(F_\tau)$  for any  $i$ ,  $\alpha(\tau^i(\Omega)) \subseteq \beta(F_\tau)$ . By definition of the limit, this implies  $\lim_i \alpha(\tau^i(\Omega)) \subseteq \beta(F_\tau)$ , and,  $\alpha$  being continuous,

$$\alpha(F_\tau) = \alpha(\lim_i \tau^i(\Omega)) = \lim_i \alpha(\tau^i(\Omega)) \subseteq \beta(F_\tau).$$

Example 1. We wish to show that the program

$$F(x) \Leftarrow \text{if } p(x) \text{ then } x \text{ else } F(F(h(x)))$$

defines an idempotent function, i.e., that  $F_\tau F = F_\tau$ . By  $p$  and  $h$ , we understand respectively any naturally extended partial predicate and function. We prove  $P(F_\tau)$ , where  $P(F)$  is  $F_\tau F = F$ , i.e.,  $(F_\tau F \subseteq F) \wedge (F \subseteq F_\tau F)$ .

- Show  $P(\Omega)$  (i.e.,  $F_\tau \Omega = \Omega$ ).

$$F_\tau(\Omega(x)) = F_\tau(\omega) \quad \text{definition of } \Omega$$

$$\in \text{if } p(\omega) \text{ then } \omega \\ \text{else } F_\tau(F_\tau(h(\omega)))$$

definition of  $F_\tau$

$$\in \text{if } \omega \text{ then } \omega \\ \text{else } F_\tau(F_\tau(h(\omega)))$$

since  $p(\omega) = \omega$

$$\in \omega \quad \text{definition of} \\ \text{if } \omega \text{ then } a \text{ else } b$$

$$= \Omega(x) \quad \text{definition of } \Omega$$

(b) Show  $\forall F [P(F) \Rightarrow P(\tau[F])]$ , i.e.,

$$\forall F [F_\tau F = F \Rightarrow F_\tau \tau[F] = \tau[F]]$$

$$\begin{aligned} F_\tau(\tau[F](x)) &= F_\tau(\text{if } p(x) \text{ then } x \text{ ~~~~} \\ &\quad \text{else } F(F(h(x)))) \\ &\quad \text{definition of } \tau \\ &= \text{if } p(x) \text{ then } F_\tau(x) \\ &\quad \text{else } F_\tau(F(F(h(x)))) \\ &\quad \text{distributing } F_\tau \\ &\quad \text{over conditional,} \\ &\quad \text{since } F_\tau(\omega) = \omega \\ &= \text{if } p(x) \text{ then } x \\ &\quad \text{else } F_\tau(F(F(h(x)))) \\ &\quad \text{definition of } F_\tau \\ &= \text{if } p(x) \text{ then } x \\ &\quad \text{else } F(F(h(x))) \\ &\quad \text{induction hypothesis} \\ &= \tau[F](x) . \quad \text{definition of } \tau \quad \square \end{aligned}$$

The next example uses as domain the set  $\Sigma^*$  of finite strings over a given finite alphabet  $\Sigma$ , including the empty string  $\Lambda$ . There are three basic functions:

- $h(x)$  gives the head (first letter) of the string  $x$ ;
- $t(x)$  gives the tail of the string  $x$  (i.e.,  $x$  with its first letter removed);
- $a \cdot x$  concatenates the letter  $a$  to the string  $x$ .

For example,  $h(BCD) = B$ ,  $t(BCD) = CD$ ,  $B \cdot C D = BCD$ . These functions satisfy the following properties, for every  $x \in \Sigma$  and  $y \in \Sigma^*$ :

$$\begin{aligned} h(x \cdot y) &= x, \quad t(x \cdot y) = y, \quad x \cdot y \neq \Lambda, \\ \text{and } y \neq \Lambda &= h(y) \cdot t(y) = y \end{aligned}$$

Example 2. The program

$$P(x, y) \Leftarrow (\text{if } x = \Lambda \text{ then } y \text{ else } h(x) \cdot P(t(x), y))$$

defines the append function  $F_\tau(x, y)$ , denoted  $x \cdot y$ . We shall show that append is associative

<sup>2/</sup> This system is sometimes called 'linear LISP'. There is no difficulty involved in generalizing our proofs to real LISP programs.

(i.e., that  $x \cdot (y \cdot z) = (x \cdot y) \cdot z$ ) by proving  $P(F_\tau)$ , where  $P(F)$  is  $F(x, y) \cdot z = F(x, y \cdot z)$ .

(a)  $P(\Omega)$  :

$$\begin{aligned} \Omega(x, y) \cdot z &= \omega \cdot z && \text{definition of } \Omega \\ &= \text{if } \omega = \Lambda \text{ then } z \\ &\quad \text{else } h(\omega) \cdot (t(\omega) \cdot z) \\ &\quad \text{definition of } \text{append} \\ &= \omega && \text{since } \omega = \Lambda \text{ is } \omega \\ &= \Omega(x \cdot y, z) . && \text{definition of } \Omega \end{aligned}$$

(b)  $\forall F [P(F) \Rightarrow P(\tau[F])]$  :

$$\begin{aligned} \tau[F](x, y \cdot z) &= \text{if } x = \Lambda \text{ then } y \cdot z \\ &\quad \text{else } h(x) \cdot P(t(x), y \cdot z) \\ &\quad \text{definition of } \tau \\ &= \text{if } x = \Lambda \text{ then } y \cdot z \\ &\quad \text{else } h(x) \cdot (P(t(x), y) \cdot z) \\ &\quad \text{induction hypothesis} \\ &= \text{if } x = \Lambda \text{ then } y \cdot z \\ &\quad \text{else } (h(x) \cdot P(t(x), y)) \cdot z \\ &\quad \text{definition of } \text{append} \\ &= (\text{if } x = \Lambda \text{ then } y \\ &\quad \text{else } h(x) \cdot P(t(x), y)) \cdot z \\ &\quad \text{distributing } \text{append} \\ &\quad \text{over conditional,} \\ &\quad \text{since } \omega \cdot z = \omega \\ &= \tau[F](x, y) \cdot z . && \text{definition of } \tau \quad \square \end{aligned}$$

This proof was done formally with the LCF proof checker (Milner (1972a)).

#### Parallel Induction

We shall now present an application of computation induction to proving properties of two programs:  $F \Leftarrow \tau[F]$  and  $G \Leftarrow \sigma[G]$ . To prove  $P(F, G)$ , where  $P(F, G)$  is an admissible predicate, <sup>3/</sup> it is sufficient to:

<sup>3/</sup> That is, a conjunction of inequalities  $\alpha[F, G] \leq \beta[F, G]$ , where  $\alpha$  and  $\beta$  are continuous functionals.

(a) Prove  $P(\Omega, \Omega)$  ;  
 (b) Show that  $P(F, G)$  implies  $P(\tau[F], \sigma[G])$  for any  $F$  and  $G$ .

That is,

From  $P(\Omega, \Omega)$  and  $(\forall F, G)[P(F, G) \Rightarrow P(\tau[F], \sigma[G])]$   
 Infer  $P(F_\tau, G_\sigma)$ .

Example 3. Consider the programs

$F(y_1, y_2, y_3) \Leftarrow \text{if } y_1 = 0 \text{ then } y_2$   
 $\quad \quad \quad \text{else } F(y_1-1, y_2+y_3, y_3)$   
 $G(y_1, y_2, y_3) \Leftarrow \text{if } y_1 = 0 \text{ then } y_2$   
 $\quad \quad \quad \text{else } G(y_1-1, y_2+2y_1-1).$

We want to show that both programs may be used to compute the squaring function; more precisely, that  $F_\tau(x, 0, x) = G_\sigma(x, 0)$  for any natural number  $x$ . Let

$P(F, G) : \forall x \forall y [F(y, x(x-y), x) = G(y, x^2 - y^2)]$ .

We shall prove  $P(F_\tau, G_\sigma)$  which, for  $y = x$ , simplifies to  $F_\tau(x, 0, x) = G_\sigma(x, 0)$ .

(a)  $P(\Omega, \Omega) : \Omega(y, x(x-y), x) = \Omega(y, x^2 - y^2)$  by definition of  $\Omega$ .

(b)  $(\forall F, G)[P(F, G) \Rightarrow P(\tau[F], \sigma[G])]$  :

$\tau[F](y, x(x-y), x) \Leftarrow \text{if } y = 0$   
 $\quad \quad \quad \text{then } x(x-0)$   
 $\quad \quad \quad \text{else } F(y-1, x(x-y)+x, x)$   
 $\Leftarrow \text{if } y = 0$   
 $\quad \quad \quad \text{then } x^2$   
 $\quad \quad \quad \text{else } F(y-1, x(x-(y-1)), x)$   
 $\Leftarrow \text{if } y = 0$   
 $\quad \quad \quad \text{then } x^2$   
 $\quad \quad \quad \text{else } G(y-1, x^2 - (y-1)^2)$   
 $\quad \quad \quad \text{induction hypothesis}$   
 $\Leftarrow \text{if } y = 0$   
 $\quad \quad \quad \text{then } x^2 - 0^2$   
 $\quad \quad \quad \text{else } G(y-1, (x^2 - y^2) + 2y - 1)$   
 $\Leftarrow G(y, x^2 - y^2)$ .  $\square$

Example 4. Consider the two programs (Morris [1971])

$F(x, y) \Leftarrow \text{if } p(x) \text{ then } y \text{ else } h(F(k(x), y))$   
 $G(x, y) \Leftarrow \text{if } p(x) \text{ then } y \text{ else } G(k(x), h(y))$ ,

where  $p$  stands for any naturally extended partial predicate, and  $h$  and  $k$  for any naturally extended partial functions. In order to prove that  $F_\tau(x, y) = G_\sigma(x, y)$  for all  $x$  and  $y$ , we shall consider

$P(F, G) : \forall x \forall y [\{F(x, y) = G(x, y)\} \wedge \{G(x, h(y)) = h(G(x, y))\}]$ .

We prove  $P(F_\tau, G_\sigma)$ , which implies  $F_\tau = G_\sigma$  as follows:

(a)  $P(\Omega, \Omega) :$

$\{\Omega(x, y) = \Omega(x, y)\} \wedge \{\Omega(x, h(y)) = h(\Omega(x, y))\}$ ,  
 since  $h(\omega) = \omega$ .

(b)  $(\forall F, G)[P(F, G) \Rightarrow P(\tau[F], \sigma[G])]$  :

(1)  $\tau[F](x, y) \Leftarrow \text{if } p(x) \text{ then } y$   
 $\quad \quad \quad \text{else } h(F(k(x), y))$   
 $\Leftarrow \text{if } p(x) \text{ then } y$   
 $\quad \quad \quad \text{else } h(G(k(x), y))$   
 $\quad \quad \quad \text{induction hypothesis}$   
 $\Leftarrow \text{if } p(x) \text{ then } y$   
 $\quad \quad \quad \text{else } G(k(x), h(y))$   
 $\quad \quad \quad \text{induction hypothesis}$   
 $\Leftarrow G(x, y)$ .

(2)  $\sigma[G](x, h(y)) \Leftarrow \text{if } p(x) \text{ then } h(y)$   
 $\quad \quad \quad \text{else } G(k(x), h^2(y))$   
 $\Leftarrow \text{if } p(x) \text{ then } h(y)$   
 $\quad \quad \quad \text{else } h(G(k(x), h(y)))$   
 $\quad \quad \quad \text{induction hypothesis}$   
 $\Leftarrow h(\sigma[G](x, y))$ .  $\square$

#### Computational Induction for a Set of Recursive Definitions

We shall state the computational induction principle for a program consisting of two recursive definitions,

$$\begin{cases} F_1 \Leftarrow \tau_1[F_1, F_2] \\ F_2 \Leftarrow \tau_2[F_1, F_2] \end{cases} ;$$

the generalization to a system of  $n$  ( $n > 2$ ) recursive definitions is straightforward.

To prove  $P(F_{\tau_1}, F_{\tau_2})$ , where  $P(F_1, F_2)$  is an admissible predicate, it is sufficient to:

(a) Prove  $P(\Omega, \Omega)$

(b) Show that, for all  $F_1$  and  $F_2$ ,

$P(F_1, F_2)$  implies  $P(\tau_1[F_1, F_2], \tau_2[F_1, F_2])$ .

That is,

from  $P(\Omega, \Omega)$  and  $(\forall F_1, F_2) [P(F_1, F_2) \Rightarrow P(\tau_1[F_1, F_2], \tau_2[F_1, F_2])]$ ,

infer  $P(F_{\tau_1}, F_{\tau_2})$ .

In the following examples, we omit variables and parentheses whenever possible.

Example 5. Consider the program

$$\left\{ \begin{array}{l} F_1 \Leftarrow \text{if } p \text{ then } F_1 F_2 h \text{ else } F_2 g \\ F_2 \Leftarrow \text{if } q \text{ then } f F_2 F_1 \text{ else } f h \\ F_3 \Leftarrow \text{if } p \text{ then } F_3 f F_4 h \text{ else } f F_4 g \\ F_4 \Leftarrow \text{if } q \text{ then } f F_4 F_3 \text{ else } h \end{array} \right.$$

in which  $p$  and  $q$  stand for any naturally extended partial predicates, and  $f, g$  and  $h$  for any naturally extended partial functions. To prove that  $F_{\tau_1} = F_{\tau_3}$ , let  $P(F_1, F_2, F_3, F_4)$  be  $(F_1 = F_3) \wedge (F_2 = f F_4)$ ; we show that  $P(F_{\tau_1}, F_{\tau_2}, F_{\tau_3}, F_{\tau_4})$  as follows:

(a)  $P(\Omega, \dots, \Omega)$  :

$(\Omega = \Omega) \wedge (\Omega = \Omega)$  is true since  $f(\omega) = \omega$ .

(b)  $(\forall F_1, \dots, F_4) [P(F_1, \dots, F_4) \Rightarrow$

$P(\tau_1[F_1, \dots, F_4], \dots, \tau_4[F_1, \dots, F_4])]$  :

$$\begin{aligned} \tau_1[F_1, F_2, F_3, F_4] &= \text{if } p \text{ then } F_1 F_2 h \text{ else } F_2 g \\ &= \text{if } p \text{ then } F_3 f F_4 h \text{ else } f F_4 g \\ &\quad \text{induction hypothesis} \end{aligned}$$

$= \tau_3[F_1, F_2, F_3, F_4]$

$$\begin{aligned} \tau_2[F_1, F_2, F_3, F_4] &= \text{if } q \text{ then } f F_2 F_1 \text{ else } f h \\ &= f(\text{if } q \text{ then } F_2 F_1 \text{ else } h) \\ &= f(\text{if } q \text{ then } f F_4 F_3 \text{ else } h) \\ &\quad \text{induction hypothesis} \\ &= f(\tau_4[F_1, F_2, F_3, F_4]). \end{aligned}$$

□

### Transformations which Leave $F_{\tau}$ Invariant

We can use computational induction to prove useful theorems about recursive definitions. For example, if we modify a recursive definition  $F \Leftarrow \tau[F]$  by replacing some occurrences of  $F$  in  $\tau[F]$  by either  $\tau[F]$  or  $F_{\tau}$ , the function computed by the new program is precisely the original  $F_{\tau}$ .

To prove this, let us write  $\tau[F] = \tau'[F, F]$ , where we use the second argument in  $\tau'[F, F]$  to distinguish the occurrences of  $F$  which we wish to replace. We define  $\tau_1[F] = \tau'[F, \tau[F]]$  and  $\tau_2[F] = \tau'[F, F_{\tau}]$ ; our goal is to show that  $F_{\tau} = F_{\tau_1} = F_{\tau_2}$ . We show this in two steps:

(a)  $(F_{\tau_1} \subseteq F_{\tau})$  and  $(F_{\tau_2} \subseteq F_{\tau})$ . This part is

easy since by definition of  $\tau_1$  and  $\tau_2$ ,  $F_{\tau} = \tau_1[F_{\tau}] = \tau_2[F_{\tau}]$ . That is,  $F_{\tau}$  is a fixedpoint of both  $\tau_1$  and  $\tau_2$ , therefore, it is more defined than both  $F_{\tau_1}$  and  $F_{\tau_2}$ .

(b)  $(F_{\tau} \subseteq F_{\tau_1})$  and  $(F_{\tau} \subseteq F_{\tau_2})$ . This can be

shown by computational induction. (Hint: prove  $P(F_{\tau}, F_{\tau_1}, F_{\tau_2})$  where  $P(F_1, F_2, F_3)$  is  $(F_1 \subseteq F_2) \wedge (F_1 \subseteq F_3) \wedge (F_1 \subseteq \tau[F_1]) \wedge (F_1 \subseteq F_{\tau})$ .)

Example 6. To prove that  $F(x) \Leftarrow \text{if } x > 10 \text{ then } x-10 \text{ else } F(F(x+13))$  and  $G(x) \Leftarrow \text{if } x > 10 \text{ then } x-10 \text{ else } G(x+3)$  define the same function over the natural numbers, one just has to replace  $F(x+13)$  by the value of  $F_{\tau}(x+13)$ , which is  $x+3$  since  $x+13 > 10$ . □

Example 7. Consider the following program (Morris [1971])<sup>14</sup> over the positive natural numbers:

$$\begin{aligned} F_1(x) &\Leftarrow \text{if } x = 1 \text{ then } 0 \\ &\quad \text{else (if even}(x) \\ &\quad \quad \text{then } F_1(x/2) \\ &\quad \quad \text{else } F_1(3x+1)) \end{aligned}$$
$$F_2(x) \Leftarrow \text{if } x = 1 \text{ then } 0 \text{ else } F_2(F_3(x))$$

<sup>14</sup> It is not known whether the function  $F_{\tau}(x)$  is defined for all  $x$  or not; a computer program checked that it is defined for all positive integers up to  $3 \times 10^8$ .

$F_2(x) \Leftarrow \text{if } x = 1 \text{ then } 1$   
                   else (if even(x)  
                     then  $x/2$   
                   else  $F_2(F_2(\frac{x+1}{2})))$  .

We shall prove that  $F_{\tau_1} = F_{\tau_2}$  by transforming the definition of  $F_1$  and  $F_2$  respectively, until we reach the same recursive definition.

First,  $F_{\tau_1} = F_{\tau_1}$ , where:

$\tau_1^*[F](x) = (\text{if } x = 1 \text{ then } 0$   
                   else (if even(x)  
                     then  $F(x/2)$   
                   else  $\tau_1^*[F](3x+1)))$  .

Since  $\{\text{odd}(x) \text{ and } x > 1\}$  imply  $\{\text{even}(3x+1)$  and  $3x+1 > 1\}$ ,

$\tau^*[F](x) = (\text{if } x = 1 \text{ then } 0$   
                   else (if even(x)  
                     then  $F(x/2)$   
                   else  $F(\frac{3x+1}{2}))$  .

Also  $F_{\tau_2} = F_{\tau_2}$ , where  $\tau_2^*[F_2, F_3] = \tau_2^*[F_2, \tau_3^*[F_3]]$ , i.e.,

$\tau_2^*[F_2, F_3](x) = (\text{if } x = 1$   
                   then 0  
                   else (if even(x)  
                     then  $F_2(x/2)$   
                   else  $F_2(F_2(F_3(\frac{x+1}{2}))))$  .

Again  $F_{\tau_2} = F_{\tau_2}$  where

$\tau_2^*[F_2, F_3](x) = (\text{if } x = 1$   
                   then 0  
                   else (if even(x)  
                     then  $F_2(x/2)$   
                   else  $F_{\tau_2}(F_{\tau_3}(\frac{x+1}{2})))$  .

The result  $F_{\tau_2} F_{\tau_3} = F_{\tau_2}$  is easily established from the definition of  $F_2$  by considering the three cases for  $x = 1$ : true, false, undefined(w). Thus

$\tau_2^*[F_2, F_3](x) = (\text{if } x = 1 \text{ then } 0$   
                   else (if even(x)  
                     then  $F_2(x/2)$   
                   else  $F_{\tau_2}(\frac{3x+1}{2}))$  .

Finally, we consider

$\sigma^*[F_2, F_3](x) = (\text{if } x = 1 \text{ then } 0$   
                   else (if even(x)  
                     then  $F_2(x/2)$   
                   else  $F_2(\frac{3x+1}{2}))$  .

Clearly  $\sigma^*[F_2, F_3] = \tau^*[F_2]$ ; since  $F_{\tau_1} = F_{\tau}$  and  $F_{\tau_2} = F_{\sigma}$ , we establish  $F_{\tau_1} = F_{\tau_2}$  as desired.  $\square$

Example 8. To prove  $F_{\tau_1} = F_{\tau_3}$  for the program:

$\begin{cases} F_1 \Leftarrow \text{if } p \text{ then } F_3 F_2 F_2 f \text{ else } g \\ F_2 \Leftarrow \text{if } q \text{ then } F_3 h \text{ else } k \\ F_3 \Leftarrow \text{if } p \text{ then } F_1 F_4 f \text{ else } g \\ F_4 \Leftarrow \text{if } q \text{ then } F_2 F_3 h \text{ else } F_2 k \end{cases}$

we first change the definitions of  $F_1$  and  $F_4$  to

$F_1 \Leftarrow \text{if } p \text{ then } F_3 F_{\tau_2} F_2 f \text{ else } g$

and

$F_4 \Leftarrow \text{if } q \text{ then } F_{\tau_2} F_3 h \text{ else } F_{\tau_2} k$  ,

respectively, and then prove by computational induction that:

$(F_1 = F_3) \wedge (F_{\tau_2} F_2 = F_4) .$

The reader should be aware of the difficulties involved in proving that  $F_{\tau_1} = F_{\tau_3}$  without the above modifications.  $\square$

#### Truncation Induction

If for some continuous functional  $\tau$  we define the sequence of functions  $f^i$  by letting  $f^0 = \tau^0(\Omega)$ , i.e.,

$f^0 = \Omega$  and  $f^{i+1} = \tau[f^i]$  for all  $i \in \mathbb{N}$ ,

then the same argument used to establish the validity of computational induction also shows the validity of the following very similar rule:

from  $P(f^0)$  and  $(\forall i \in \mathbb{N}) (P(f^i) \Rightarrow P(f^{i+1}))$ ,  
infer  $P(F_\tau)$ .

The resemblance of this rule to the usual mathematical induction on natural numbers suggests that we consider a similar rule using complete induction over natural numbers.<sup>7/</sup> Morris [1971] called it truncation induction. More precisely,

In order to prove  $P(F_\tau)$ ,  $P(F)$  being an admissible predicate, we show that for any natural number  $i$ , the truth of  $P(f^j)$  for all  $j < i$  implies the truth of  $P(f^i)$ . That is,

from  $(\forall i \in \mathbb{N}) [(\forall j < i) P(f^j)] \Rightarrow P(f^i)$ ,  
infer  $P(F_\tau)$ .

The validity of this rule is established by first using induction on  $\mathbb{N}$  to show that  $P(f^n)$  holds for all  $n \in \mathbb{N}$ ; one can then use the proof given above for the validity of computational induction.

When the program consists of a system of recursive definitions such as

$$\left\{ \begin{array}{l} F_1 \leq \tau_1[F_1, \dots, F_k] \\ \vdots \\ F_k \leq \tau_k[F_1, \dots, F_k], \end{array} \right.$$

we let  $f^0$  be  $\langle \Omega, \dots, \Omega \rangle$ ,  $f^{i+1}$  be  $\langle \tau_1[f^i], \dots, \tau_k[f^i] \rangle$ , and  $F_\tau$  be  $\langle F_{\tau_1}, \dots, F_{\tau_k} \rangle$ ; the truncation induction rule is then precisely the same as above.

Example 3. (Morris [1971]). We consider again (see Example 4) the two programs:

$F(x, y) \leq (\text{if } p(x) \text{ then } y \text{ else } h(F(k(x), y)))$   
 $G(x, y) \leq (\text{if } p(x) \text{ then } y \text{ else } G(k(x), h(y))),$

where  $p$  stands for any naturally extended partial predicate, and  $h$  and  $k$  for any naturally extended partial functions.

In order to prove that both programs define the same function, we check that  $f^0 = g^0$ ,

<sup>7/</sup> When applied to natural numbers, these two inductions are equivalent; thus truncation induction and computational induction are equivalent from a theoretical point of view. Experience in using both methods shows that they are also equivalent in practice.

$f^1 = g^1$  and that  $f^n = g^n$  for all  $n \geq 2$ . (We treat the cases for  $n = 0$  and  $n = 1$  separately, since to prove  $f^n = g^n$  we have to use the induction hypothesis for both  $n-1$  and  $n-2$ .)

(a)  $f^0 = g^0 : \Omega = \Omega$ .

(b)  $f^1 = g^1 :$

$$\begin{aligned} f^1(x, y) &= \text{if } p(x) \text{ then } y \text{ else } h(f^0(k(x), y)) \\ &= \text{if } p(x) \text{ then } y \text{ else } \omega \\ &= \text{if } p(x) \text{ then } y \text{ else } g^0(k(x), h(y)) \\ &= g^1(x, y). \end{aligned}$$

(c)  $f^n = g^n$  for  $n \geq 2$ :

$$\begin{aligned} f^n(x, y) &= \text{if } p(x) \text{ then } y \text{ else } h(f^{n-1}(k(x), y)) \\ &\quad \text{definition of } f^n \\ &= \text{if } p(x) \text{ then } y \text{ else } h(g^{n-1}(k(x), y)) \\ &\quad \text{induction hypothesis (n-1)} \\ &= \text{if } p(x) \text{ then } y \\ &\quad \text{else } h(\text{if } p(k(x)) \\ &\quad \quad \text{then } y \\ &\quad \quad \text{else } g^{n-2}(k^2(x), h(y))) \\ &\quad \quad \text{definition of } g^{n-1} \\ &= \text{if } p(x) \text{ then } y \\ &\quad \text{else } (\text{if } p(k(x)) \\ &\quad \quad \text{then } h(y) \\ &\quad \quad \text{else } hg^{n-2}(k^2(x), h(y))) \\ &= \text{if } p(x) \text{ then } y \\ &\quad \text{else } (\text{if } p(k(x)) \\ &\quad \quad \text{then } h(y) \\ &\quad \quad \text{else } hf^{n-2}(k^2(x), h(y))) \\ &\quad \quad \text{induction hypothesis (n-2)} \\ &= \text{if } p(x) \text{ then } y \text{ else } f^{n-1}(k(x), h(y)) \\ &\quad \quad \text{definition of } f^{n-1} \\ &= \text{if } p(x) \text{ then } y \text{ else } g^{n-1}(k(x), h(y)) \\ &\quad \quad \text{induction hypothesis (n-1)} \\ &= g^n(x, y). \quad \text{definition of } g^n \quad \square \end{aligned}$$

It is often useful to define slightly different sequences of functions  $f^i$  and then apply a generalized form of truncation induction, as illustrated in the next example. Kleene's first recursion theorem can again be used to establish the

validity of such generalized truncation induction rules.

Example 10. We consider again the program

$F \Leftarrow \text{if } p \text{ then } J \text{ else } FFh$ ,

where  $J$  is the identity function. We shall prove that  $F_t F_t = F_t$ . For this purpose we define the sequence of functions  $f^i$  in the following way:

$$f^0 = \Omega$$

$$f^1 = \tau[\Omega]$$

$$f^{n+2} = \text{if } p \text{ then } J \text{ else } f^{n+1} f^n h \text{ for } n \geq 0;$$

note that for  $n \geq 2$ , it is not necessarily the case that  $f^n = \tau^n[\Omega]$ .

We shall prove the desired result by generalized truncation induction, letting the induction hypothesis be  $f^{n+3} f^{n+2} = f^{n+4}$ .

We first check the cases  $n = 0$  and  $n = 1$  (the details are omitted); then, assuming that the induction hypothesis is true for all  $i < n$ , we get

$$\begin{aligned} f^{n+3} f^{n+2} &= f^{n+3} (\text{if } p \text{ then } J \text{ else } f^{n+1} f^n h) \\ &\quad \text{definition of } f^{n+2} \\ &= \text{if } p \text{ then } f^{n+3} \text{ else } f^{n+3} f^{n+1} f^n h \\ &= \text{if } p \text{ then } J \text{ else } f^{n+3} f^{n+1} f^n h \\ &\quad \text{definition of } f^{n+3} \\ &= \text{if } p \text{ then } J \text{ else } f^{n+3} f^{n+2} h \\ &\quad \text{induction hypothesis} \\ &= f^{n+4}. \quad \text{definition of } f^{n+4} \end{aligned}$$

By complete induction, it follows that  $f^{n+3} f^{n+2} = f^{n+4}$  for all  $n \in \mathbb{N}$ ; then Kleene's theorem can be used to establish that  $F_t F_t = F_t$ , as desired.  $\square$

### III. STRUCTURAL INDUCTION

One familiar method of proving assertions on the domain  $\mathbb{N}$  of natural numbers is that of complete induction: in order to prove that the statement  $P(c)$  is true for every natural number  $c$ , we show that for any natural number  $a$ , the truth of  $P(b)$  for all  $b < a$  implies the truth of  $P(a)$ .

That is,

from  $(\forall a \in D)[[(\forall b < a)P(b)] \Rightarrow P(a)]$ ,  
infer  $(\forall c \in D)P(c)$ .

Since this induction rule is not valid for every ordered domain,  $\square$  we shall first characterize the ordered domains which are 'good' for induction. We then present a general rule for proving statements over such domains, called structural induction; complete induction, as well as many other well-known induction rules, is a special case of structural induction. Finally, we give several examples using structural induction to prove properties of recursively defined functions.

#### Well-founded Sets

A partially ordered set  $(S, \leq)$  consists of a set  $S$  and a partial ordering  $\leq$  on  $S$ .  $\square$  A partially ordered set  $(S, \leq)$  which contains no infinite decreasing sequence  $a_0 > a_1 > a_2 > \dots$  of elements of  $S$  is called a well-founded set.

Examples. (a) The set of all real numbers between 0 and 1, with the usual ordering  $\leq$ , is partially ordered but not well-founded (consider the infinite decreasing sequence  $\frac{1}{2} > \frac{1}{3} > \frac{1}{4} > \dots$ ).

(b) The set  $\mathbb{Z}$  of integers, with the usual ordering  $\leq$ , is partially ordered but not well-founded (consider  $0 > -1 > -2 > \dots$ ).

(c) The set  $\mathbb{N}$  of natural numbers, with the usual ordering  $\leq$ , is well-founded.

(d) If  $\Sigma$  is any alphabet, then the set  $\Sigma^*$  of all finite strings over  $\Sigma$  (i.e., sequences of letters of  $\Sigma$ ), with the substring relation ( $w_1 \leq w_2$  iff  $w_1$  is a substring of  $w_2$ ), is well-founded.  $\square$

#### Structural Induction

We may now state and prove the rule of structural induction on well-founded sets.  $\square$  Suppose

$\square$  e.g., it is valid over the natural numbers with ordering  $\leq$  but fails over the integers with ordering  $\leq$  (consider  $P$  which is always false).

$\square$  Note that the ordering need not be total, i.e., it is possible that for some  $a, b \in S$ , neither  $a \leq b$  nor  $b \leq a$  holds.

$\square$  Structural induction is sometimes also called Noetherian induction. When the ordering  $\leq$  is total, i.e.,  $a \leq b$  or  $b \leq a$  holds for any  $a, b \in S$ , it is called transfinite induction.

$P$  is a total predicate over the well-founded set  $(S, <)$ . If for any  $a$  in  $S$ , we can prove that the truth of  $P(a)$  is implied by the truth of  $P(b)$  for all  $b < a$ , then  $P(c)$  is true for every  $c$  in  $S$ . That is:

From  $(\forall a \in S) [(\forall b \in S \text{ s.t. } b < a) P(b)] = P(a)$ ,  
 infer  $(\forall c \in S) P(c)$ .

To prove the validity of this rule, we show that if the assumption is satisfied, there can be no element in  $S$  for which  $P$  does not hold. Consider the set  $A$  of elements  $a \in S$  such that  $P(a)$  is false. Let us assume that  $A$  is nonempty. Then, there is a least element  $a_0$  such that  $a \neq a_0$  for any  $a \in A$ : otherwise, there would be an infinite descending sequence in  $S$ . Then, for any element  $b$  such that  $b < a_0$ ,  $P(b)$  must hold; that is,  $(\forall b \in S \text{ s.t. } b < a_0) P(b)$ . But the assumption then implies that  $P(a_0)$ , in contradiction with the fact that  $a_0 \in A$ . Therefore  $A$  must be empty, i.e.,  $P(c)$  must hold for all elements  $c \in S$ .

#### Applications

We now give several examples using structural induction to prove properties of recursive programs. Such proofs require suitable choices of both the partial ordering  $<$  and of the predicate  $P$ . Some of the examples show that the partial ordering to be chosen is not always the usual partial ordering on the domain. Other examples illustrate that it is often useful to prove a more general result than the desired theorem.

#### Example 1. (Cadiou) Factorial functions.

Consider the two programs

$F_1(x) \Leftarrow \text{if } x = 0 \text{ then } 1 \text{ else } x \cdot F_1(x-1)$

and

$$\begin{cases} F_2(x) \Leftarrow F_3(x, 0, 1) \\ F_3(x, y, z) \Leftarrow \text{if } x = y \text{ then } z \text{ else } F_3(x, y+1, (y+1) \cdot z) \end{cases}$$

$F_{t_1}$  and  $F_{t_2}$  compute  $x! = 1 \cdot 2 \cdot \dots \cdot x$  for every  $x \in \mathbb{N}$  in two different ways:  $F_{t_2}$  by 'going up' from 0 to  $x$  and  $F_{t_1}$  by 'going down' from  $x$  to 0. We wish to show that  $F_{t_2} = F_{t_1}$ . The proof uses the predicate  $P(x)$ :

$(\forall y \text{ s.t. } y \geq x) [F_{t_3}(y, y-x, F_{t_1}(y-x)) = F_{t_1}(y)]$ ,

and the usual ordering on natural numbers.

(a) If  $x = 0$ ,  $P(0)$  is  $\forall y [F_{t_3}(y, y-x, F_{t_1}(y)) = F_{t_1}(y)]$ , which is clearly true by definition of  $F_{t_3}$ .

(b) If  $x > 0$ , we assume  $P(x')$  for all  $x' < x$  and show  $P(x)$ .

For any  $y$  s.t.  $y \geq x$ ,

$$\begin{aligned} F_{t_3}(y, y-x, F_{t_1}(y-x)) &= F_{t_3}(y, y-x+1, (y-x+1) \cdot F_{t_1}(y-x)) \\ &\quad \text{definition of } F_{t_3} \\ &\quad (\text{since } x > 0) \end{aligned}$$

$$= F_{t_3}(y, y-x+1, F_{t_1}(y-x+1))$$

definition of  $F_{t_1}$

(since  $y-x+1 > 0$ )

$$= F_{t_3}(y, y-(x-1), F_{t_1}(y-(x-1)))$$

$$= F_{t_1}(y) \quad \text{induction hypothesis} \\ (\text{since } (x-1) < x \text{ and } (x-1) \leq y)$$

By complete induction then,  $P(x)$  holds for all  $x \in \mathbb{N}$ . In particular, for  $y = x$ ,  $F_{t_3}(x, 0, F_{t_1}(0)) = F_{t_1}(x)$ . Since  $F_{t_1}(0) = 1$  and  $F_{t_3}(x, 0, 1) = F_{t_2}(x)$ , we have  $F_{t_2} = F_{t_1}$  as desired.  $\square$

Given a partially ordered set  $(S, <)$ , we define the lexicographic ordering  $\leq$  on  $n$ -tuples of elements of  $S$  (i.e., on elements of  $S^n$ ) by letting  $(a_1, \dots, a_n) \leq (b_1, \dots, b_n)$  iff  $a_1 = b_1 \wedge \dots \wedge a_{i-1} = b_{i-1} \wedge a_i < b_i$  for some  $i$ ,  $1 \leq i \leq n$ . It is easy to show that if  $(S, <)$  is well-founded, so is  $(S^n, \leq)$ . For example,

- (a) For the natural numbers with the usual ordering  $\leq$ , the set  $(\mathbb{N}^2, \leq)$  is well-founded:  $(n_1, n_2) \leq (m_1, m_2)$  iff  $n_1 < m_1$  or  $(n_1 = m_1) \wedge (n_2 < m_2)$  (note that e.g.  $(1, 100) \leq (2, 1)$ ).
- (b) For the alphabet  $\Sigma = \{A, B, \dots, Z\}$  with the usual ordering  $A < B < C < \dots < Z$ , the set

$(\Sigma^3, \leq)$  of words of length three is well-founded. Note that this is the usual alphabetic order: e.g., AAK  $\leq$  BAT  $\leq$  CAD  $\leq$  CAT .

Example 2. Ackermann's function.

Consider the program

```
A(x,y) <= if x = 0 then y+1
           else if y = 0 then A(x-1,1)
           else A(x-1,A(x,y-1)).
```

We wish to show that  $A_\tau(x,y)$  is defined for any  $x,y \in \mathbb{N}$ , i.e., that the computation of  $A_\tau(x,y)$  always terminates. We shall use the structural induction rule applied on  $(\mathbb{N}^2, \leq)$ . Assuming that  $A_\tau(x',y')$  is defined for any  $(x',y')$  such that  $(x',y') \leq (x,y)$ , we show that  $A_\tau(x,y)$  must also be defined.

- (a) If  $x = 0$ , termination is obvious.
- (b) If  $x \neq 0$  and  $y = 0$ , we note that  $(x-1,1) \leq (x,y)$ , so by the induction hypothesis  $A_\tau(x-1,1)$  is defined. Thus  $A_\tau(x,y)$  is also defined.
- (c) Finally, if  $x \neq 0$  and  $y \neq 0$ ,  $(x,y-1) \leq (x,y)$  and  $A_\tau(x,y-1)$  is therefore defined by the induction hypothesis; then, regardless of the value of  $A_\tau(x,y-1)$ ,  $(x-1,A_\tau(x,y-1)) \leq (x,y)$  and the desired result follows by another application of the induction hypothesis.  $\square$

In each of the preceding examples we used the most natural ordering on the domain to perform the structural induction. In the next example it is natural to use a somewhat surprising ordering.

Example 3. (Burstall). The 91-function.

The 91-function  $F_\tau$  is defined by the following program over the integers:

```
F(x) <= if x > 100 then x-10 else F(F(x+11)) .
```

We wish to show that  $F_\tau = g$ , where  $g$  is

```
g(x) = if x > 100 then x-10 else 91 .
```

The proof is by structural induction on the well-founded set  $(\mathbb{I}, \leq)$ , where  $\mathbb{I}$  is the integers and  $\leq$  is defined as follows:

$x \leq y$  iff  $y < x \leq 101$

(where  $\leq$  is the usual ordering on the integers); thus  $101 \leq 100 \leq 99 \leq \dots$ , but for example,  $102 \not\leq 101$ . One can easily check that  $(\mathbb{I}, \leq)$  is well-founded.

Suppose  $F_\tau(y) = g(y)$  for all  $y \in \mathbb{I}$  such that  $y \leq x$ . We must show that  $F_\tau(x) = g(x)$ .

- (a) For  $x > 100$ ,  $F_\tau(x) = g(x)$  directly.
- (b) For  $100 \geq x \geq 90$ ,  $F_\tau(x) = F_\tau(F_\tau(x+11)) = F_\tau(x+1)$ , and since  $x+1 < x$  we have  $F_\tau(x) = F_\tau(x+1) = g(x+1)$  by the induction assumption. But  $g(x+1) = 91 = g(x)$ , therefore  $F_\tau(x) = g(x)$ .
- (c) Finally, for  $x < 90$ ,  $F_\tau(x) = F_\tau(F_\tau(x+11))$ , and since  $x+11 < x$  we have  $F_\tau(x) = F_\tau(F_\tau(x+11)) = F_\tau(g(x+11))$  by induction. But  $g(x+11) = 91$ , and we know by induction that  $F_\tau(91) = g(91) = 91$ , so  $F_\tau(x) = F_\tau(g(x+11)) = F_\tau(91) = 91 = g(x)$ , as desired.

We could alternatively have proven the above property by structural induction on the natural numbers with the usual ordering  $\leq$ , using the more complicated predicate  $P(n)$ :  $(\forall x \in \mathbb{I})[x > 100 - n \Rightarrow F_\tau(x) = g(x)]$ . The reader should note that the details of this proof and of the above proof are precisely the same.  $\square$

Since the set  $(\Sigma^*, \leq)$  of finite strings  $\Sigma$  with the substring relation is well-founded, we may use it for structural induction. In the following example we use an induction rule that can easily be derived from structural induction, namely:

from  $P(A)$  and  $(\forall x \in \Sigma^*)[x \neq A \wedge P(t(x)) \leq P(x)]$   
infer  $(\forall x \in \Sigma^*)P(x)$ .

Example 4. The reverse function.

The program reverse,

```
{ reverse(x) <= F(x,A)
  F(x,y) <= if x = A then y else F(t(x),h(x)-y) ,
```

gives as value over  $\Sigma^*$  the string made up of the letters of  $x$  in reverse order. For example, if  $\Sigma = \{A,B,C\}$  then  $\text{reverse(ACB)} = BCA$ .

We wish to prove that reverse( $x$ ) is defined and that reverse(reverse( $x$ )) =  $x$  for all  $x \in \Sigma^*$ . Of course, proving that reverse has this property

does not show that it actually reverses all words: many other functions, e.g. the identity function, also satisfy this property.

1. To prove that  $\underline{\text{reverse}}(x)$  is always defined, we let

$P(x)$  be  $(\forall y \in \Sigma^*)[F_t(x, y) \text{ is defined}]$ .

- (a) If  $x = \Lambda$ , then  $F_t(x, y) = y$ , and thus  $F_t(x, y)$  is defined.
- (b) If  $x \neq \Lambda$ , since  $t(x) < x$  we may assume that  $F_t(t(x), z)$  is defined for any  $z$ ; therefore  $F_t(t(x), h(x) \cdot y)$  is defined for all  $y \in \Sigma^*$ . Thus  $F_t(x, y)$  is defined for any  $y$ .

It follows by structural induction that  $F_t(x, y)$  is defined for all  $x, y \in \Sigma^*$ , and in particular, since  $\underline{\text{reverse}}(x) = F_t(x, \Lambda)$ ,  $\underline{\text{reverse}}(x)$  is defined for all  $x \in \Sigma^*$ .

2. To prove  $\underline{\text{reverse}}(\underline{\text{reverse}}(x)) = x$  we let

$P(x)$  be  $(\forall y \in \Sigma^*)[\underline{\text{reverse}}(F_t(x, y)) = F_t(y, x)]$ .

- (a) If  $x = \Lambda$ , then for any  $y$  we have  $\underline{\text{reverse}}(F_t(x, y)) = \underline{\text{reverse}}(y) = F_t(y, \Lambda) = F_t(y, x)$ .
- (b) If  $x \neq \Lambda$ , then for any  $y$  we have
 
$$\begin{aligned}
 & \underline{\text{reverse}}(F_t(x, y)) \\
 &= \underline{\text{reverse}}(F_t(t(x), h(x) \cdot y)) \\
 & \quad \text{definition of } F_t \\
 & \quad (\text{since } x \neq \Lambda) \\
 &= F_t(h(x) \cdot y, t(x)) \\
 & \quad \text{induction hypothesis} \\
 & \quad (\text{since } x > t(x)) \\
 &= F_t(y, h(x) \cdot t(x)) \\
 & \quad \text{definition of } F_t \\
 & \quad (\text{since } h(x) \cdot y \neq \Lambda) \\
 &= F_t(y, x) .
 \end{aligned}$$

Therefore  $\underline{\text{reverse}}(F_t(x, y)) = F_t(y, x)$  for all  $x, y \in \Sigma^*$ ; in particular, for  $y = \Lambda$ ,  $\underline{\text{reverse}}(\underline{\text{reverse}}(x)) = \underline{\text{reverse}}(F_t(x, \Lambda)) = F_t(\Lambda, x) = x$ , as desired.  $\square$

Other properties of  $\underline{\text{reverse}}$  may easily be proven by structural induction. In particular, the following example uses the properties that,

for any  $a, b \in \Sigma$  and  $x \in \Sigma^*$ :

- (i)  $\underline{\text{reverse}}(x \cdot a) = a \cdot \underline{\text{reverse}}(x)$ ,
- (ii)  $\underline{\text{reverse}}(a \cdot x) = \underline{\text{reverse}}(x) \cdot a$ , and
- (iii)  $\underline{\text{reverse}}(a \cdot (x \cdot b)) = b \cdot (\underline{\text{reverse}}(x) \cdot a)$ .

Example 5. Another reverse function.

We wish to show that the program (due to Ashcroft)

```
R(x) <= if x = \Lambda
      then \Lambda
      else if t(x) = \Lambda
            then x
            else h(R(t(x))) \cdot R(h(x) \cdot R(t(R(t(x)))))
```

also defines a reversing function on  $\Sigma^*$ , i.e., that  $R(x) = \underline{\text{reverse}}(x)$  for all  $x \in \Sigma^*$ . Note that this program uses only one recursive definition.

In the proof we shall use the following lemma characterizing the elements of  $\Sigma^*$ : for any  $x \in \Sigma^*$ , either  $x = \Lambda$ , or  $x \in \Sigma$  (i.e.,  $t(x) = \Lambda$ ), or  $x = y \cdot (w \cdot z)$  for some  $y \in \Sigma$ ,  $w \in \Sigma^*$ , and  $z \in \Sigma$ . The lemma is easy to prove by a straightforward structural induction.

We now prove that  $R_t = \underline{\text{reverse}}$  by structural induction on  $(\Sigma^*, <)$ , where  $<$  is the following partial ordering:

$x < y$  iff  $x$  is a substring of  $y$  or  $x$  is a substring of  $\underline{\text{reverse}}(y)$ . One can check that  $(\Sigma^*, <)$  is well-founded.

Using the above lemma, the proof may be done in three parts.

- (a)  $x = \Lambda$ :  $R_t(x) = \Lambda = \underline{\text{reverse}}(x)$ .
- (b)  $x \in \Sigma$ :  $R_t(x) = x = \underline{\text{reverse}}(x)$ .
- (c)  $x = y \cdot (w \cdot z)$  for some  $y \in \Sigma$ ,  $w \in \Sigma^*$ ,  $z \in \Sigma$ :

$$\begin{aligned}
 R_t(x) &= h(R_t(t(x))) \cdot R_t(h(x) \cdot R_t(t(R_t(t(x))))) \\
 & \quad \text{definition of } R_t \\
 &= h(R_t(w \cdot z)) \cdot R_t(y \cdot R_t(t(R_t(w \cdot z)))) \\
 & \quad \text{since } h(x) = y, t(x) = w \cdot z \\
 &= h(\underline{\text{reverse}}(w \cdot z)) \cdot R_t(y \cdot R_t(t(\underline{\text{reverse}}(w \cdot z)))) \\
 & \quad \downarrow \quad \text{induction hypothesis} \\
 & \quad (\text{since } w \cdot z < x)
 \end{aligned}$$

$\equiv h(z \cdot \text{reverse}(w)) \cdot R_{\tau}(y \cdot R_{\tau}(t(z \cdot \text{reverse}(w))))$   
 property (i) of reverse  
 $\equiv z \cdot R_{\tau}(y \cdot R_{\tau}(\text{reverse}(w)))$   
 properties of h and t  
 $\equiv z \cdot R_{\tau}(y \cdot \text{reverse}(\text{reverse}(w)))$   
 induction hypothesis  
 (since reverse(w)  $\prec$  x)  $\checkmark$   
 $\equiv z \cdot R_{\tau}(y \cdot w)$   
 property of reverse  
 proven in previous  
 example  
 $\equiv z \cdot \text{reverse}(y \cdot w)$  induction hypothesis  
 (since y  $\cdot$  w  $\prec$  x)  
 $\equiv z \cdot (\text{reverse}(w) \cdot y)$  property (ii) of reverse  
 $\equiv \text{reverse}(x)$  property (iii) of reverse

We conclude that  $R_{\tau}(x) = \text{reverse}(x)$  for all  $x \in \Sigma^*$ , as desired.  $\square$

#### Comparison between Computational Induction and Structural Induction

Although computational induction and structural induction appear to be quite different methods, we shall show how any proof using one method can be translated to a proof using the other.

##### (a) Translation from Computational Induction to Structural Induction

Using the principle of structural induction and the hypothesis  $P(\Omega)$  and  $\forall F \{P(F) \Rightarrow P(\tau(F))\}$ , where  $P(F)$  is taken to be  $\alpha[F] \subseteq \mathcal{B}[F]$  for simplicity, we must prove  $P(F_{\tau})$ . For that purpose, we shall consider a well-founded ordering  $\prec$  over  $D^*$  which resembles the computation of  $\alpha[F_{\tau}]$  as follows:  $x \prec y$  iff the Kleene computation sequence  $\checkmark$  of  $\alpha[F_{\tau}](x)$  is shorter than that of  $\alpha[F_{\tau}](y)$ . Using the definition, it is straightforward to show that  $(\forall x \in D^*) \{(\forall y \in D^* \text{ such that } y \prec x) Q(y) = Q(x)\}$ , where  $Q(x)$  is  $\alpha[F_{\tau}](x) \subseteq \mathcal{B}[F_{\tau}](x)$ : by structural induction, it follows that  $(\forall x \in D^*) Q(x)$ , i.e.,  $P(F_{\tau})$ .

$\checkmark$  Note that reverse(w)  $\prec$  x, which is true because reverse(w) is a substring of reverse(x), as may be seen from property (c) of reverse.

$\checkmark$  i.e.,  $\exists n \text{ s.t. } \tau^n(\Omega)(x) \neq \omega$  and  $\tau^n(\Omega)(y) = \omega$ .

##### (b) Translation from Structural Induction to Computational Induction

Unlike computational induction, structural induction may be used to prove general mathematical theorems, rather than just properties of programs. However, if we restrict ourselves to proving properties of programs,  $\checkmark$  Wilner [1970b] has shown that structural induction can be nicely replaced by computational induction. The next two examples illustrate the use of this technique in cases where more direct computational induction fails.

##### Example 6. Factorial functions.

Consider again the two programs of Example 1:

$F_1(x) \Leftarrow \text{if } x = 0 \text{ then } 1 \text{ else } x \cdot F_1(x-1)$ ,

and

$$\begin{cases} F_2(x) \Leftarrow F_2(x, 0, 1), \\ F_3(x, y, z) \Leftarrow \text{if } x = y \text{ then } z \\ \text{else } F_3(x, y+1, (y+1) \cdot z). \end{cases}$$

Since  $F_{\tau_1}$  and  $F_{\tau_2}$  are computed differently, the equivalence  $F_{\tau_1} = F_{\tau_2}$  cannot be proven directly by computational induction. However, we can consider the domain of natural numbers to be recursively defined by the program

number(x)  $\Leftarrow$  if  $x = 0$  then true else number(x-1),

and proceed to prove by computational induction on this program that:

$$(\forall x, y) \{ (x > y \vee \text{number}(x)) \subseteq [F_{\tau_3}(y, y-x, F_{\tau_1}(y-x)) = F_{\tau_1}(y)] \}.$$

The proof can now be carried on, following the steps of the proof of Example 1.  $\square$

##### Example 7. Reverse function.

Consider again the program of Example 4 defining the reverse function:

$$\begin{cases} \text{reverse}(x) \Leftarrow F(x, \Lambda) \\ F(x, y) \Leftarrow \text{if } x = \Lambda \text{ then } y \text{ else } F(t(x), h(x) \cdot y). \end{cases}$$

We shall show that reverse(x) (i.e.,  $F_{\tau}(x, \Lambda)$ ) is defined for any  $x$  in  $\Sigma^*$ . For this purpose, we characterize the elements of  $\Sigma^*$  by the program

$\checkmark$  More precisely, when the well-founded ordering can be recursively defined.

word(x) <= o[word](x) , where

$\tau[G](x) = (\text{if } x = \Lambda \text{ then true else } G(t(x)))$ .

We let  $P(F, G)$  be  $(\forall x, y \in \Sigma^*) \{ [G(x) \wedge \text{word}(y)] \leq \text{word}(F(x, y)) \}$ .

(a)  $\underline{P(\Omega, \Omega)} : [\Omega(x) \wedge \text{word}(y)] \leq \text{word}(\Omega(x, y))$   
reduces to  $\omega \leq \omega$ .

(b)  $\underline{\forall F, G [P(F, G) \Rightarrow P(\tau[F], \tau[G])]} :$

$$\begin{aligned} & [\tau[G](x) \wedge \text{word}(y)] \\ &= \text{if } x = \Lambda \text{ then word}(y) \\ & \quad \text{else } G(t(x)) \wedge \text{word}(y) \\ & \quad \text{definition of } \tau \\ &= \text{if } x = \Lambda \text{ then word}(y) \\ & \quad \text{else } G(t(x)) \wedge \text{word}(h(x) \cdot y) \\ & \quad \text{definition of word} \\ &\leq \text{if } x = \Lambda \text{ then word}(y) \\ & \quad \text{else word}(\tau[F](x), h(x) \cdot y)) \\ & \quad \text{induction hypothesis} \\ &= \text{word}(\tau[F](x, y)) . \quad \text{definition of } \tau \end{aligned}$$

Therefore, by computational induction, we have:

$$[\text{word}(x) \wedge \text{word}(y)] \leq \text{word}(\tau_{\tau}(x, y)) \quad \text{for all } x, y \in \Sigma^*$$

which for  $y = \Lambda$  gives  $\text{word}(x) \leq \text{word}(\text{reverse}(x))$ ; i.e.,  $\text{reverse}(x)$  is defined and its value is a word whenever  $x$  is a word.  $\square$

#### IV. OTHER METHODS

In this section, we present two additional methods for proving properties of programs: recursion induction and inductive assertions. We show that any proof by either of these methods can be effectively translated into a proof by computational induction (and therefore also into a proof by structural induction).

#### Recursion Induction

To prove the equivalence of two functions  $f_1$  and  $f_2$  over some subdomain  $S$  of  $D$ , i.e., that  $f_1(x) = f_2(x)$  for all  $x \in S$ , it is sufficient to find a functional  $\tau$  such that:

- $f_1$  is a fixedpoint of  $\tau$ , i.e.,  $f_1 = \tau[f_1]$ ,
- $f_2$  is a fixedpoint of  $\tau$ , i.e.,  $f_2 = \tau[f_2]$ , and
- $\tau_{\tau}(x)$  is defined for any  $x$  in  $S$ .

The justification of this rule is easy: by definition of  $\tau_{\tau}$ , we know that  $\tau_{\tau}(x) \leq f_1(x)$  and  $\tau_{\tau}(x) \leq f_2(x)$ , for any  $x$  in  $D$ ; therefore, for any  $x$  in  $S$ , since  $\tau_{\tau}(x)$  is defined,  $\tau_{\tau}(x) = f_1(x) = f_2(x)$ .

Example 1. (McCarthy [1963b]). We consider again the function reverse, defined in Example 4 (Section 3). We wish to prove by recursion induction that

$$\text{reverse}(x \cdot y) = \text{reverse}(y) * \text{reverse}(x) \quad \text{for all } x, y \in \Sigma^*$$

For this purpose we choose the functional  $\tau$  defined by

$$\tau[F](x, y) = \text{if } x = \Lambda \text{ then reverse}(y) \\ \text{else } F(t(x), y) * h(x) .$$

Then using known properties of  $*$  and reverse, we get that

(a)  $\text{reverse}(x \cdot y)$  is a fixedpoint of  $\tau$ , since

$$\begin{aligned} \text{reverse}(x \cdot y) &= \text{if } x = \Lambda \\ & \quad \text{then reverse}(y) \\ & \quad \text{else reverse}((h(x) \cdot t(x)) \cdot y) \\ &= \text{if } x = \Lambda \\ & \quad \text{then reverse}(y) \\ & \quad \text{else reverse}(h(x) \cdot (t(x) \cdot y)) \\ &= \text{if } x = \Lambda \\ & \quad \text{then reverse}(y) \\ & \quad \text{else } (\text{reverse}(t(x) \cdot y)) * h(x) . \end{aligned}$$

(b)  $\text{reverse}(y) * \text{reverse}(x)$  is a fixedpoint of  $\tau$ , since

$$\begin{aligned} \text{reverse}(y) * \text{reverse}(x) &= \text{if } x = \Lambda \\ & \quad \text{then reverse}(y) * \Lambda \\ & \quad \text{else reverse}(y) * \text{reverse}(x) \\ &= \text{if } x = \Lambda \\ & \quad \text{then reverse}(y) \\ & \quad \text{else reverse}(y) * (\text{reverse}(t(x)) * h(x)) \end{aligned}$$

```

    = if x = A
      then reverse(y)
      else (reverse(y) * reverse(t(x))) * h(x) .
  
```

(c)  $F_t(x,y)$  is defined for every  $x,y \in \Sigma^*$ , as can be shown by a straightforward induction on  $x$ .  $\square$

Example 2. We consider a system over the natural numbers in which the primitives are the predicate zero(x) (true only when  $x$  is 0), the predecessor function pred(x) (where pred(0) is 0), and the successor function succ(x). In this system the program

```

add(x,y) <= if zero(x)
  then y
  else add(pred(x),succ(y))
  
```

defines the addition function. We wish to prove that  $\text{succ}(\text{add}(x,y)) = \text{add}(x,\text{succ}(y))$  for all  $x,y \in \mathbb{N}$  by recursion induction.

We consider the functional  $\tau$  defined as

```

 $\tau[F](x,y) = (\text{if zero}(x)$ 
  then succ(y)
  else F(pred(x),succ(y))) .
  
```

The reader can easily verify that both functions succ(add(x,y)) and add(x,succ(y)) are fixedpoints of  $\tau$ . Furthermore, an easy induction on  $x$  shows that  $F_t(x,y)$  is defined for any  $x$  and  $y$  in  $\mathbb{N}$ , which completes the proof.  $\square$

It is interesting to compare the preceding example with Example 4 of Section 2, where we considered the program

```

G(x,y) <= if p(x) then y else G(k(x),h(y))
  
```

and proved that

$hG_g(x,y) = G_g(x,h(y))$  for all  $x$  and  $y$ .

If we interpret  $p(x)$  as zero(x),  $k(x)$  as pred(x), and  $h(y)$  as succ(y),  $G_g(x,y)$  becomes add(x,y), and the proof that  $hG_g(x,y) = G_g(x,h(y))$  is actually another proof that  $\text{succ}(\text{add}(x,y)) = \text{add}(x,\text{succ}(y))$ . It is interesting to note that the algebraic manipulations used in both proofs are the same. However, the proof by recursion induction needed an argument of termination; if we consider the definition  $G(x,y) <= \text{if } p(x) \text{ then } y \text{ else } G(k(x),h(y))$  with no specific interpretation in mind for  $p$ ,  $k$  and

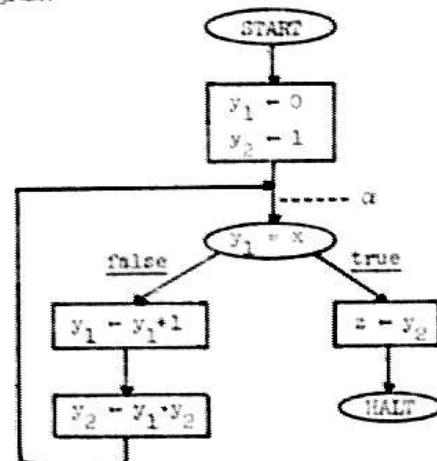
$h$ , no argument for the termination of  $G_g$  is possible (since, for instance, if  $p(x)$  is always false,  $G_g$  is never defined). A property like  $hG_g(x,y) = G_g(x,h(y))$  therefore cannot be proven by recursion induction (Morris [1971]).

An interesting special case of recursion induction, for which no proof of termination is needed, was described in Section 2. To prove the equivalence of two recursively defined functions, one can try to modify each definition until both definitions are the same, using transformations which leave the fixedpoint unchanged. This method was illustrated by Examples 6 and 7 of Section 2.

It is easy to show that every proof by recursion induction can be effectively translated to a proof by computational induction. Hint: assume  $f_1 = \tau[f_1]$  and  $f_2 = \tau[f_2]$  and prove  $P(F_t)$ , where  $P(F)$  is  $(F \leq f_1) \wedge (F \leq f_2)$ .

#### Inductive Assertion Method

The most widely used method for proving properties of flowchart programs, called the inductive assertions method, was suggested by Floyd [1967]. We shall illustrate the method and its relation to computational induction on a simple flowchart program.



We wish to show that the above flowchart program over the natural numbers computes the factorial function, i.e.,  $z = x!$ , whenever it terminates. To do this, we associate a predicate called an inductive assertion  $Q(x,y_1,y_2)$  with the point labelled  $\alpha$  in the program, and show that  $Q$  must be true for the values of the variables  $x,y_1,y_2$  whenever execution of the program reaches point  $\alpha$ . Thus, we must show (a) that the assertion holds

when point  $\alpha$  is first reached after starting execution (i.e., that  $Q(x, 0, 1)$  holds) and (b) that it remains true when one goes around the loop from  $\alpha$  to  $\alpha$  (i.e., that  $y_1 \neq x \wedge Q(x, y_1, y_2)$  implies  $Q(x, y_1+1, (y_1+1) \cdot y_2)$ ). To prove the desired result we finally show (c) that  $z = x!$  follows from the assertion  $Q(x, y_1, y_2)$  when the program terminates (i.e., that  $y_1 = x \wedge Q(x, y_1, y_2)$  implies  $y_2 = x!$ ).

We take  $Q_F(x, y_1, y_2)$  to be  $y_2 = y_1!$ . Then:

- (a)  $Q_F(x, 0, 1)$  is  $1 = 0!$ .
- (b) We assume  $y_1 \neq x$  and  $Q_F(x, y_1, y_2)$ , i.e.,  $y_2 = y_1!$ . Then  $Q_F(x, y_1+1, (y_1+1) \cdot y_2)$  is  $(y_1+1) \cdot y_2 = (y_1+1)!$ , i.e.,  $(y_1+1) \cdot y_1! = (y_1+1)!$ .
- (c) We assume  $y_1 = x$  and  $Q_F(x, y_1, y_2)$ , i.e.,  $y_2 = y_1!$ ; then  $y_2 = y_1! = x!$  as desired.

To show that the proof by inductive assertions corresponds to a computational induction proof in a natural way, we must first translate the flowchart program into a recursive program. Following the technique of McCarthy [1963a], we find that the output  $z$  of the above flowchart program is computed by the program

$$\begin{cases} \text{fact}(x) \Leftarrow F(x, 0, 1), \\ F(x, y_1, y_2) \Leftarrow \text{if } y_1 = x \\ \quad \text{then } y_2 \\ \quad \text{else } F(x, y_1+1, (y_1+1) \cdot y_2) \end{cases}.$$

We shall prove by computational induction that  $F_F(x, 0, 1) \subseteq x!$ , i.e., that the value of  $F_F(x, 0, 1)$  is  $x!$  whenever  $F_F(x, 0, 1)$  is defined. We take  $P(F)$  to be the following admissible predicate:

$$(\forall x, y_1, y_2 \in \mathbb{N}) [\sim Q_F(x, y_1, y_2) \vee F(x, y_1, y_2) \subseteq x!].$$

Obviously  $P(\emptyset)$  holds. To show that  $P(F) = P(\tau[F])$  for every function  $F$ , we consider two cases: either  $y_1 = x$ , in which case the proof follows directly from (c) above, or  $y_1 \neq x$ , which follows directly from (b).

By computational induction we therefore have  $P(F_F)$ , i.e.,  $\sim Q_F(x, y_1, y_2) \vee F_F(x, y_1, y_2) \subseteq x!$  for all  $x, y_1, y_2 \in \mathbb{N}$ . But since  $Q_F(x, 0, 1)$  is known from (a) to hold, we conclude that  $F_F(x, 0, 1) \subseteq x!$ , as desired.

Manna and Pnueli [1970] generalized the inductive assertions method to apply to recursive programs. By their method it follows that the recursive program above computes the factorial function, when it terminates, if and only if there exists an inductive assertion  $Q(x, y_1, y_2, z)$  such that

$$\begin{aligned} & (\forall x, z \in \mathbb{N}) [Q(x, 0, 1, z) \Rightarrow z = x!] \\ & \wedge (\forall x, y_1, y_2, z \in \mathbb{N}) [\text{if } y_1 = x \\ & \quad \text{then } Q(x, y_1, y_2, y_2) \\ & \quad \text{else } \exists t [Q(x, y_1+1, (y_1+1) \cdot y_2, t) = \\ & \quad Q(x, y_1, y_2, t)]], \end{aligned}$$

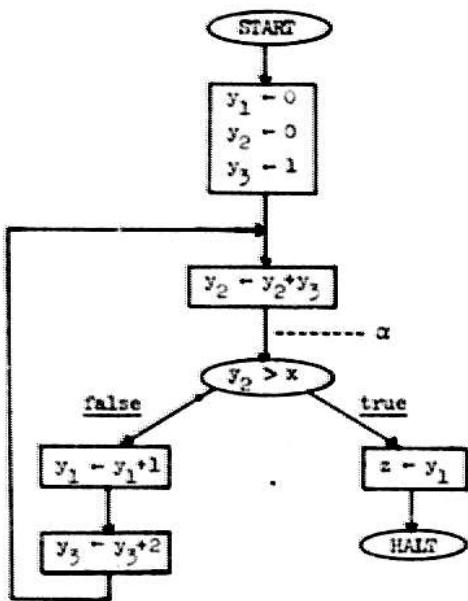
is true. (The formula implies that  $Q(x, y_1, y_2, z)$  is true whenever  $F_F(x, y_1, y_2) = z$ .)

The reader may easily check that the above formula is satisfied by taking the predicate  $Q_{NP}(x, y_1, y_2, z)$  to be  $z \cdot y_1! = y_2 \cdot x!$ , which proves that  $F_F(x, 0, 1) \subseteq x!$  as desired.  $\square$  The difference between the assertions  $Q_F(x, y_1, y_2)$  and  $Q_{NP}(x, y_1, y_2, z)$  should be noted:  $Q_F(x, y_1, y_2)$  represents all possible values of the variables  $x, y_1, y_2$  at arc  $\alpha$  during execution, while  $Q_{NP}(x, y_1, y_2, z)$  represents the relation between the final value of  $z$  and the initial value of  $x, y_1$  and  $y_2$  when computation starts at arc  $\alpha$ .

As in the case of flowchart programs, the proof by the Manna-Pnueli method can easily be translated into a proof by computational induction, taking the predicate  $P(F)$  to be  $(\forall x, y_1, y_2 \in \mathbb{N}) [F(x, y_1, y_2) \cdot y_1! \subseteq y_2 \cdot x!]$ .

To further illustrate the use of the inductive assertion method, we briefly present a less familiar example. We shall show that for any natural number  $x$  the flowchart program given below, whenever it terminates, computes the smallest natural number greater than  $\sqrt{x}$ , i.e., that  $z^2 \leq x < (z+1)^2$ .

$\square$  Given an inductive assertion  $Q_F(x, y_1, y_2)$  for the flowchart program, one can take the predicate  $Q_{NP}(x, y_1, y_2, z)$  given by  $Q_F(x, y_1, y_2) = (z = x!)$  and check that it also satisfies the above formula. However, the predicate obtained in this way is less natural than the predicate  $Q_{NP}$  given above.



We must show that there is an inductive assertion  $Q(x, y_1, y_2, y_3)$  such that:

$$\begin{aligned}
 & (\forall x \in \mathbb{N}) Q(x, 0, 1, 1) \\
 & \wedge (\forall x, y_1, y_2, y_3 \in \mathbb{N}) [Q(x, y_1, y_2, y_3) \\
 & \quad \Rightarrow \text{if } y_2 > x \\
 & \quad \text{then } y_1^2 \leq x < (y_1 + 1)^2 \\
 & \quad \text{else } Q(x, y_1 + 1, y_2 + y_3 + 2, y_3 + 2)]
 \end{aligned}$$

is true. We take  $Q_p$  to be

$$(y_1^2 \leq x) \wedge (y_2 = (y_1 + 1)^2) \wedge (y_3 = 2y_1 + 1) .$$

The reader may check that this assertion shows correctness as desired.

The corresponding recursive program is

$$\begin{cases} \text{sqrt}(x) \Leftarrow F(x, 0, 1, 1) \\ F(x, y_1, y_2, y_3) \Leftarrow \text{if } y_2 > x \\ \quad \text{then } y_1 \\ \quad \text{else } F(x, y_1 + 1, y_2 + y_3 + 2, y_3 + 2) \end{cases} ,$$

and the Manna-Pnueli formula is

$$\begin{aligned}
 & (\forall x, z \in \mathbb{N}) [Q(x, 0, 1, 1, z) \Rightarrow z^2 \leq x < z] \\
 & \wedge (\forall x, y_1, y_2, y_3 \in \mathbb{N}) [\text{if } y_2 > x \\
 & \quad \text{then } Q(x, y_1, y_2, y_3, y_1) \\
 & \quad \text{else } \text{if } Q(x, y_1 + 1, y_2 + y_3 + 2, y_3 + 2, t) \\
 & \quad \quad \Rightarrow Q(x, y_1, y_2, y_3, t)]]
 \end{aligned}$$

This is satisfied by taking  $Q_{mp}(x, y_1, y_2, y_3, z)$  to be

$$\begin{aligned}
 & \text{if } y_2 > x \text{ then } y_1 = z \\
 & \text{else } (z - y_1)^2 + (z - y_1)(y_3 - 1) + (y_2 - y_3) \leq x \\
 & \quad < (z - y_1)^2 + (z - y_1)(y_3 + 1) + y_2 .
 \end{aligned}$$

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